AI based Mobile Application for Waste Management and Recycling

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DOI: https://doi.org/10.3126/mvicjmit.v1i2.85888

Abstract

Waste disposal is one of the challenges faced by most developing countries. People follow improper waste disposal practices by throwing all the waste into the landfill sites. This research introduces a mobile application integrating Artificial Intelligence (AI) to classify waste image types of recyclable objects and suggest recycling tips. It also provides a platform to schedule organic waste pickup service. It uses a lightweight MobileNetV2 model to identify the waste types. Gamification techniques, such as a point-based reward system, are developed for user engagement in the application. This research paper contributes to the growing positive use of AI in the environmental sustainability sector.

Keywords: AI, Waste disposal, Recyclable objects, Gamification, Environmental sustainability

1. Introduction

Waste is unwanted or discarded materials that no longer serve a purpose for an individual or organization. Similarly, the advent of urbanization, industrialization, and shifts in lifestyle are the root causes of the generation of tons of waste each day. The generated waste can fall into the category of recyclable, organic, or hazardous waste. Since waste production continues to grow at an alarming rate, it must be managed sustainably due to inefficient and inadequate waste production. Waste production has contributed to environmental, health, and social challenges. The situation is critical and demands immediate attention, as it is degrading the ecosystem. Visualizing the complexity of the problem, a proper governmental policy must be formulated. Innovative strategies for proper waste management should be implemented, utilizing various infrastructures and technologies. Citizens play an important role in being proactive and informed. They should actively engage in source-level segregation and sustainable practices. Through the collaboration of government bodies, organizations, and communities, waste can be properly managed in an organized way.

The cost of extracting raw materials is increasing due to their less availability and overconsumption of natural resources. Goods made from recycled products can be a better alternative, as recycling involves recovering new material from unwanted waste products. For example, old newspapers can be collected and recycled into new egg cartons, paper plates, and more; old tires can be transformed into chairs; and plastic products (non-food-grade) such as used plastic bottles can undergo mechanical recycling and be recycled back into new plastic bottles (Popa et al., 2017). The use of 3D machines, artificial intelligence, and ongoing advancements in technology has made the recycling process much easier and more systematic.

2. Objectives of the Study

The objectives are as follows:

i. To encourage users to segregate waste at the source and provide a platform to manage and up cycle organic waste.
ii. To research the AI-based image classification model to identify an effective approach for identifying waste image types.
iii. To promote user engagement and long-term participation in sustainable waste management through gamification techniques.
iv. To empower individuals and organizations to manage waste at the local level, reducing reliance on landfills.

3. Review of Literature

With the rapid increase in population and urbanization, the current waste management practices of dumping waste on landfill sites and incineration have shown a negative impact on the environment. Traditionally, Municipal Solid Waste (MSW) is collected from households or communal bins and transported to centralized facilities for treatment or disposal. According to research conducted by the Asian Development Bank (2013), approximately 70% of the household waste collected by Nepalese municipalities ends up in the stream as mixed waste. Often, the waste is then manually segregated or processed using basic machinery before it is recycled or sent for final disposal in landfills.

As evidenced by the situation in China, MSW is treated through landfilling (52%) and incineration (45%), which shows low efficiency in the management of waste as compared to the developed countries. Similarly, the high proportion of organic (41%) and inert (40%) materials, such as construction debris and road sweepings, is found in the average waste produced in Indian MSW (Kumar et al., 2017). The effective initial separation of waste shall be an option to improve the resource recovery rate.

There have been significant advancements in the smart waste management system, such as IoT-enabled bins and robotic systems that support efficient waste collection and automated segregation. Although with these great interventions, all these technologies focus on the waste after it has already been mixed at the source.

The governmental bodies, in collaboration with non-governmental organizations, have made considerable investments in conducting awareness programs and distributing color-coded bins to the general public to promote household-level segregation. Despite these efforts, there is no consistent effort to implement and practice the proper waste segregation habits among urban residents. This still shows user action as a barrier to proper waste management implementation. Moreover, families living in apartments, rented housing, young professionals, students in shared accommodation, and households without easy access to recycling facilities often fail to follow proper waste management practices. Due to the busy work-life schedule, composting and proper segregation of organic waste are not consistently practiced at the household or commercial level, even among those who understand its importance. The city of Alappuzha, as stated by C40 Cities Climate Leadership Group in India, has shown a successful example of local organic waste processing through the establishment of small-scale biogas plants and compost bins, which have now reduced landfill waste and minimized land disposal costs.

Zhang et al.(2022) studied that on-waste segregation practices in households, around 68% of the participants claimed to have knowledge about the importance of waste segregation. But they also identified “lack of time” and “confusion about categories” as the major obstacles stopping them from following proper waste sorting practices. Taufique and Vaithianathan (2018) showed that behavioral patterns can be improved through gamification techniques for better user engagement. In their study, recycling increased by 22% over a six-month trial using engaging gamification methods. However, the engagement appeared to drop again after the trial period. A mobile application should keep on working on keeping the users motivated for waste segregation and recycling. There should also be a platform for active users so that they become role models for others in the future.

Artificial Intelligence can be used to classify various types of waste. It can be used in mobile applications, smart bins, etc, to detect trash and find appropriate ways for recycling, reducing, or reusing it. Different machine learning algorithms, such as random forest, decision tree, k-nearest neighbors, and Support Vector Machine (SVM), can be used to classify the waste. Unlike Convolution Neural Networks (CNN), based on the paper published by Nasir and Al-Talib (2023) suggested that these techniques, while training with large amounts of data, give less accuracy and make the process difficult. CNNs are widely used for image classification and demonstrate high accuracy with small datasets. IOP Science, in supervised image classification techniques using CNN, an input image with its corresponding label is required to train the model to generate an accurate output class. Studies have been conducted using various algorithms such as ANN, SVMs, and RNNs for waste detection and classification. Among these, as stated by Zenghui et al. (2022). Convolutional Neural Networks (CNNs) achieved the highest level of accuracy, with a reported accuracy rate of 87% on the ImageNet dataset.

In recent days, advanced recycling innovations have been developed using AI and robotics. Yu et al. (2021) proposed an Artificial Intelligence-based Hybridized Intelligent Framework (AIHIF) for automating waste sorting on an industrial scale. CNN and robotics were used to automate the sorting process. Their system reduced human workload by 40% while maintaining the classification accuracy of 92%. Similarly, researchers at the University of Osaka developed a robot with a laser system to detect different plastic materials as advancement in recycling. Plastic polymers such as polyethylene terephthalate, high-density polyethylene, low-density polyethylene, and polypropylene can be detected using the laser sensor. The model achieved 95% detection accuracy. After identifying the material, it precisely sorts plastic for recycling and can be repurposed to make new plastic products like textiles and plastic lumber. Despite these advancements in technology, polypropylene (PP) remains underutilized because it is not widely accepted by the recycling centers. Due to its limited recycling infrastructure, efforts can still be made to make brooms and battery cables from the polymer.

Mittal et al. (2016) proposes a convincing model using a Convolutional Neural Network (CNN) to identify garbage in waste images. The goal of the application is to create fast garbage detection without consuming high memory. However, it is limited to classifying the waste from the identified trash. Instead of making a classification of waste types into multiple recycling classes. Donovan (2016) classifies them into simpler two types: recycling and compostable items. It does make the sorting problem easier, but not completely. There is still a need for further segregation of the recyclable waste before moving it to recycling.

The Trash Net dataset for training CNN models to classify waste into six categories: plastic, cardboard, trash, metal, glass, and paper. Their model achieved 63% accuracy on the dataset split under a 70/30 training/testing ratio. However, the paper suggests increasing the diversity of trash images for better accuracy. Since the dataset mainly contains Western waste types (eg, soda cans, wine bottles), its real-time application in South Asian regions has shown comparatively less. The model fails to identify region-specific waste items. Also, the real-world variability in trash image degrades the performance. Both lighting and angle should be appropriate for uploading an image. Bircanoğlu et al. (2018) compared waste sorting mechanisms in different types of CNN. 75% test accuracy was found using the ResNet50 model, but it had a hard time in real-time deployment because of its slower prediction speed. Waste sorting robots and smart bins are the AI and IoT devices suited best for use in public spaces. It is quite impractical for daily household use due to its high cost. Low-cost AI tools for waste classification, integrated into mobile-friendly applications, are much more suitable for household use.

In urban areas like Kathmandu Valley in Nepal, Shrestha et al. (2014) found that informal waste pickers collect 80% of recyclable waste. Residents in the area lacked digital tools to coordinate with the recyclers. Also, if organic waste had been properly managed, the energy generated from it could have powered more than 1,000 homes. So, residents should also initiate collaboration with the non-governmental organizations for further improvement in implementation. People are still making a solid effort in systematically managing waste, but a fully convincing, proper, perfect solution has yet to be achieved. Cudjoe et al. (2023) proposed a behavioral analysis of residents and developed a mobile application for the residents in China. A GPS-tracked pickup request system was implemented to connect households with informal recyclers. This has reduced the landfill waste by 35%. The data suggests that there is potential in adding AI tools for the user, focusing on their waste reusability and awareness.

4. Research Methodology

The idea and major goal became simpler with a proper direction and a clearer vision. This led to changes in the plan and development during the project. Agile methodology supports exactly this approach. It offers an iterative cycle of the Software Development Life Cycle, where planning, development, testing, and evaluation are repeated and carried out continuously throughout the project. The project was broken down into smaller, manageable chunks. The development was carried out chunk by chunk in increasing order. Then, the testing was done continuously. Based on the feedback received, further changes were implemented and tested. Important and prioritized tasks were tackled first. By following the Agile methodology, it became easier to identify necessary changes and ensure the project stayed aligned with its intended scope and benefits.

5. Implementation and Testing

The mobile application's backend was built to manage user interactions, waste scheduling, waste classification, and administrative tasks. Models were created to structure tables in the database. Serializers were used to convert model instances to JSON format and vice versa for API communication. Viewsets and class-based views have all the core functionalities and operations, such as user registration, login, and waste item prediction, scheduling waste, route optimization, and predicting image type. These API were first tested in Postman. After successful data responses, APIs were connected to the React Native frontend.API interactions for the respective users are secured using JWT tokens. The app dynamically renders screens based on the data returned from the API.

When an image is uploaded from a user's camera or gallery, it is sent through an API to the backend. Then, the image is predicted into its respective category. Again, the view response with predicted waste category ID, accuracy percentage, and its image ID.

When a waste pickup is scheduled for a particular day, the latitude and longitude data of all scheduled users are collected to determine the optimized route for the waste collection vehicle.

The waste classification model was initially trained on the Trash Net dataset. The dataset contains approximately 2500 labelled images categorized into six classes. However, the size of the dataset was found to be limited. So, the volume of the dataset was increased manually from the images found in the public dataset from Kaggle. As a result, the total dataset size increased to 8,803 images, 252.2% greater than the original dataset images. Also, the diverse variations of the trash image were added to each category to improve classification accuracy. The variations of image type are based on waste images of multiple angles and deformations in the image, including crumpled paper and crushed cans. Waste types are divided into glass, cardboard, metal, paper, plastic, and trash categories. The sample images of the waste data frame are shown in Figure 1 in a grid layout. It verifies that the loaded images are free from anomalies and displays a 3x3 grid of randomly selected images from different categories.

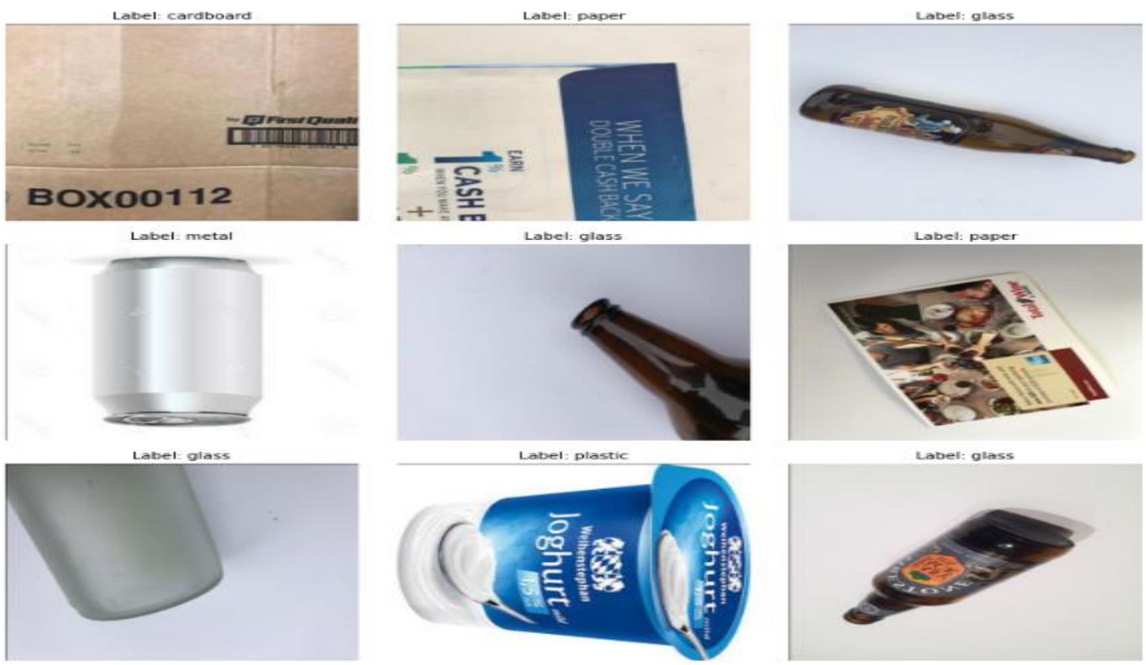

Figure 1: Unprocessed Trash Images

Then, the dataset was split into training and testing sets in an 80:20 ratio. The class is balanced while splitting the data, as a function is used to iterate over each waste class in the Data frame to collect 80% of the image volume in each category. After splitting the dataset, both training and testing Data Frames are shuffled to a randomized sample order for generalizing the model.

Data augmentation was applied in the training set to expand the variations in the waste data images. 45-degree angle rotation, image zooming, and horizontal/vertical flipping were used to simulate different orientations of the waste items. The pixel values were rescaled to the range [0,1]. Also, the images were sized to 224x224 pixels to meet the input size requirement of the MobileNetV2 model.

In [13]:
```python
Model =Sequential([
    MobileNetV2(weights = 'imagenet', include_top=False, input_shape=(224,224,3)),
    Flatten(),
    Dense(64,activation = 'relu'),
    BatchNormalization(),
    Dropout(0.08),
    Dense(6, activation = 'softmax')
])
```

In [14]:
```python
preTrainedModel = Model.layers[0]
for layer in preTrainedModel.layers[:-4]:
    layer.trainable = False
```

In [15]:
```python
Model.compile(optimizer='adam',loss='categorical_crossentropy' ,metrics=['accuracy'])
```

In [16]:
```python
history = Model.fit(trainGenerator,
                    validation_data = testGenerator,
                    epochs=50,
                    verbose=1,
                    callbacks=[tf.keras.callbacks.EarlyStopping(
                                  patience=4,
                                  monitor='val_accuracy',
                                  restore_best_weights=True)])
```

Figure 2: Training the model

All the layers are frozen except the last four layers of the pre-trained MobileNetV2 model to fine-tune waste classification. The model was trained for a maximum of 50 epochs on the training dataset and evaluated on the validation set.

After training, the model achieved 96.18% training accuracy and 91.88% validation accuracy. The validation loss range of 0.3 displays that there is no under fitting or over fitting of the data. 96.18% training accuracy and 91.88% validation accuracy are achieved using the model. There is a 4.3% minimal performance gap.

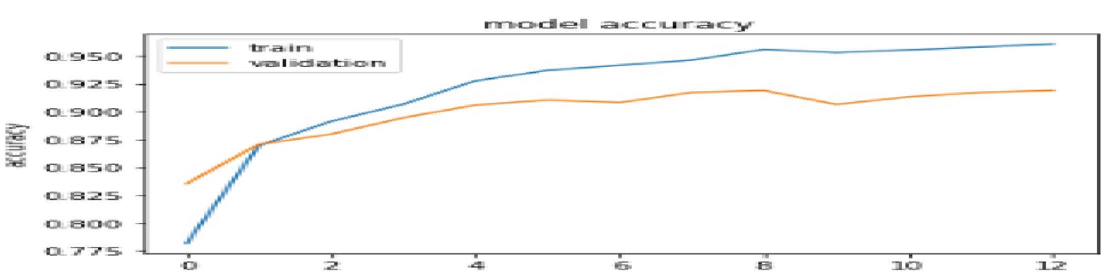

Figure 3: Training/ Validation Accuracy Graph

6. Conclusion

In conclusion, a successful waste management application was prototyped with continuous learning, testing, and implementation of different languages, frameworks, and improvements throughout the project lifecycle. The application encourages individuals and organizations to develop responsible waste disposal habits. It demonstrates a way to use AI to tackle the burning real-world problem of waste management. Also, it shows the importance of geo-location services and user engagement in the waste management ecosystem.

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