AI-Driven Multi-Class Waste Classification for Sustainable Recycling Infrastructure in Post-Conflict Zones Using CNN, IoT, and AR

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***Abstract*— Regions affected by conflict leads to increasing amount of waste accumulation. This has a profound impact that goes beyond the geographical boundaries. The restoration process comes with a lot of challenges. For environmental restoration and reconstruction, we need efficient waste recycling and debris management strategies. This research proposes a strategic model for recycling and reuse in post-conflict zones. The AI-powered deep learning model aims to classify mixed household waste by utilizing a dataset containing 15,150 images from 12 household garbage categories. The model's predictions make use of Convolutional neural network (CNN) to train and classify waste with high accuracy. The trained model can segregate waste into recyclable, biodegradable, and non-recyclable groups. Our solution aims to foster sustainability and assist in urban recovery by serving as a guide to strategic planning for mobile recovery units and local recycling networks. By integrating the proposed approach with IoT devices and augmented reality (AR) interfaces, this study outlines a smart material recovery system optimized for waste management of construction debris, thereby being a generally applicable solution for post-disaster environments.**

I. INTRODUCTION

Post-conflict zones often face immense challenges in managing waste, particularly the waste accumulation from destroyed infrastructure in commercial and residential zones resulting in a massive buildup of debris, household garbage, and hazardous materials. This leads to significant environmental stress from unmanaged waste and rubble. While such regions strive towards reconstruction and societal restoration, the need for a sustainable, intelligent waste management framework becomes imperative. Application of cutting-edge technologies like Artificial Intelligence(AI), Internet of Things(IoT), Augmented Reality(AR) promise transformative approaches to help rebuild these areas. The proposed research focuses on utilizing advanced deep learning methodologies to automate waste management and segregation thereby supporting environmental rehabilitation. Our work is built upon Convolutional Neural Networks (CNNs) architecture, utilizing the dataset containing 15,150 labeled images with 12 categories of common waste including glass, metal, plastic, cardboard, clothes, thrash, shoes, battery, biological waste often encountered in conflict – affected areas. The proposed model with AI, IoT sensors and AR can overcome the challenges faced by these regions due to hazardous containments, by enabling real-time tracking, visual guidance and necessary interactive decision-support tools. The model can be referred to as a knowledge base for policymakers and recovery agencies. Our framework helps to accelerate the sustainable rehabilitation and development process for a more resilient future.

II. LITERATURE REVIEW

Post-conflict zones often face massive environmental and infrastructural degradation with health, environmental, and logistical challenges. The United Nations Environment Program (UNEP) reported more than 80 million tons of debris [1]. Traditional systems struggle to process challenges efficiently. Recent studies highlight the potential of Artificial Intelligence (AI) and CNN-based models for multi-class garbage identification, with IoT-integrated AI systems for smart bin monitoring and predictive waste collection [2]. AI and IoT have been successfully applied to enhance the resilience of energy systems [3], which parallels the need for robust, smart waste infrastructure in unstable post-conflict zones. AI-powered image classification systems can achieve accuracy levels above 90% in segregating waste types, drastically improving operational efficiency and safety [4]. Like AI's role in optimizing agriculture [5], intelligent models can be applied to streamline the recovery and sorting of construction waste in post-conflict settings, ensuring sustainable resource reuse. Predictive analytics models can forecast waste generation patterns based on historical data, population density, and conflict recovery activities. AI to predict when bins will reach capacity and to dynamically adjust collection schedules is discussed in [6]. Integration of Internet of Things (IoT) devices with AI models can monitor real-time parameters such as fill level, temperature, and the presence of hazardous substances and determine the optimal time for collection, trigger alerts in case of dangerous conditions [7]. IoT-powered monitoring systems used in marine ecosystems [8] can inform similar deployments in debris recovery, ensuring minimal environmental impact and efficient logistics in post-disaster zones. Although there are significant barriers to the significant implementation of these technological solutions. The scarcity of localized data, the heterogeneity of waste types (household garbage to chemical, biological, and explosive remnants). All this requires specific context data that is often unavailable. Also, deploying robotic systems or AI-powered devices in areas with ongoing security threats poses serious risks and requires the development of robust operational protocols. Despite these challenges, several case studies have demonstrated the feasibility and effectiveness of AI-driven waste management solutions in fragile and conflict-affected areas. The United Nations Satellite Centre (UNOSAT) has used AI-powered image analysis and satellite imagery to map debris and destruction [9]. Edge computing and decentralized deep learning networks [10] allow waste detection models to function in real-time, even in remote or infrastructure-damaged areas. The integration of blockchain with IoT systems [11] can ensure secure, tamper-proof waste tracking and reporting, especially critical in resource-constrained, post-conflict environments. Blockchain-based architectures [12] can protect sensitive sensor data gathered from waste-laden areas, especially when dealing with hazardous or biomedical waste. Establishing trust through blockchain mechanisms [13] is critical in ensuring fair resource reuse and transparent decision-making during post-conflict reconstruction. Also, IoT's role in optimizing renewable energy [14] can be extended to real-time environmental sensing and waste recovery in degraded or disaster-hit zones. AI has been applied to optimize sustainable agriculture systems in Oman [15], illustrating its adaptability to complex, resource-intensive tasks such as intelligent waste recovery and recycling. AI can also support post-conflict waste management indirectly through augmented reality (AR) and digital training tools. Workers operating in hazardous environments can use AR headsets integrated with AI to receive real-time guidance on sorting procedures, safety protocols, and contamination detection. Transfer learning techniques, where pre-trained models are fine-tuned on small, local datasets, offer a promising solution to the data scarcity problem. Recent scholarly work has also explored how advanced machine learning and deep learning models, including reinforcement learning, can be adapted to optimize resource-intensive applications like waste management in complex environments [16]. The development of AI-based material recovery models that can assess the recyclability and economic value of construction and demolition debris can inform decision-making processes regarding which materials to reclaim and reuse in rebuilding efforts, thus closing the loop between waste management and sustainable reconstruction. The integration of AI with drone-based surveillance, blockchain for waste traceability, and renewable energy systems for powering smart devices also holds significant promise for creating resilient and scalable recycling infrastructures.

III. Methodology

The proposed system uses deep learning, augmented reality (AR), and Internet of Things (IoT) technologies to classify and manage waste in post-conflict zones. The core objective is to automate the classification of waste into various categories using a Convolutional Neural Network (CNN). Once classified, waste is grouped into recyclable, biodegradable, and non-recyclable. This provides real-time decision-making for disposal or recovery via IoT devices and AR visualizations. The system architecture shown below processes input waste images, predicts the waste class, and uses smart sensors and AR overlays to enable intelligent, location-aware waste management operations.

A. System Architecture

The system architecture represented in figure 1 shown, processes waste images, classifies them into multiple categories like glass, metal, plastic, cardboard, clothes, thrash, shoes, battery etc., and then integrates them with IoT and AR technologies for waste management in post-conflict zones.

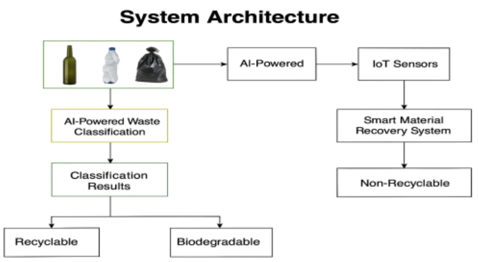

Figure 1: Proposed Architecture

B. Dataset Overview

We have made use of a dataset available at "https://www.kaggle.com/datasets/mostafaabla/garbage-classification" . The system is trained on this dataset of 15,150 labeled images. To start with, all images are preprocessed by resizing the images to 128x128 pixels. Pixel values of the images are normalized by scaling them to the range [0, 1]. Data augmentation techniques such as rotation, flipping, and zooming are applied. The processed dataset is split into two parts - 80% : 20% for training and testing respectively.

C. Model Architecture

A sequential model allows us to add layers one after another in a linear fashion, which is perfect for building CNNs. The convolution operation is computed using equation (1), where I denote the input image matrix, K denotes the filter (kernel) matrix, F is the filter size.

$$I''_{\{i,j\}} = (I * K)_{\{i,j\}} = sum_{\{m=0\}^{\{F-1\}sum}_{\{n=0\}^{\{F-1\}I}_{\{i+m,j+n\}}}} * K_{\{m,n\}} \quad (1)$$

$$f(x) = max(0, x) \quad (2)$$

$$I''_{\{i,j\}} = max_{\{p,q\}\{}I'_{\{i+p,j+q\}\}} \quad (3)$$

The ReLU (Rectified Linear Unit) activation function is used to introduce non-linearity into the model defined by equation (2), where x is the input value. This function sets all negative values to 0, while keeping positive values unchanged and helps with issues like vanishing gradients in deep networks. To reduce the spatial dimensions of the feature maps The MaxPooling layer shown in equation (3) is used. It helps prevent overfitting by sliding a window over the feature map and selecting the maximum value within that window.
Softmax converts raw scores into probabilities for multi-class classification. categorical_crossentropy is a loss function used for multi-class classification. Adaptive learning rate optimizer (Adam) is used.

The following shows the CNN model algorithm

1. Start
2. Initialize model
3. Add Conv2D layer + ReLU + MaxPooling
4. Repeat for 3–4 layers
5. Flatten
6. Add Dense layers + Dropout
7. Add Softmax output layer (12 units for 12 classes)
8. Compile with categorical_crossentropy, Adam optimizer
9. Train the model using training data
10. Stop

D. Classification and Grouping

Once the CNN model predicts the waste image as one of 12 categories, a logical grouping is applied to organize these classes into meaningful waste management groups. Let C be the predicted class label then, G(C) is the group function as shown below.

G(C) =
{
"Recyclable", if C ∈ {glass, metal, plastic, cardboard}
"Biodegradable", if C ∈ {food waste, biological}
"Non-recyclable", if C ∈ {trash, shoes, clothes, batteries}
}

The CNN comprises three convolutional and max-pooling layers, followed by a dense layer and a softmax classifier. ReLU activation is used to introduce non-linearity, while max-pooling reduces spatial dimensions. The Adam optimizer and categorical cross-entropy loss function are employed for model training.

E. AR Integration

AR overlays for field technicians using mobile/tablet AR SDK (e.g., Vuforia, ARCore). This enhances the safety and usability of personnel working in hazardous or chaotic post-conflict environments. Once the CNN model classifies the type of waste, AR-based mobile or tablet applications—developed using SDKs such as ARCore, Vuforia, or Unity AR Foundation—superimpose critical information directly into the user's field of view.

F. IOT Integration

Smart bins, mobile collection units, or autonomous drones are equipped with embedded sensors (e.g., weight sensors, ultrasonic fill-level detectors, chemical/gas sensors, GPS modules) to track environmental and operational parameters. Once waste is deposited into smart bins, sensors automatically detect the waste type and volume, validating CNN predictions through physical measurements or sensor fusion. The bins are connected via low-power communication protocols (e.g., LoRaWAN, Zigbee, or NB-IoT), transmitting data to a centralized or edge server. If a bin is full or contains hazardous materials, it can trigger real-time alerts to nearby mobile units or central control systems, allowing timely intervention.

IV. Results and Discussion

A. Model Performance

The proposed Convolutional Neural Network (CNN) was trained on a dataset of 15,150 labeled waste images spanning 12 classes. The initial training epoch achieved a classification accuracy of 42.8% with a loss of 1.77. This baseline performance reflects the model's early learning phase. Over subsequent epochs, both training and validation accuracy improved significantly, demonstrating the model's ability to extract discriminative features from complex waste images.
The model's convergence behavior is consistent with standard learning curves observed in deep CNNs. As training progressed, categorical cross entropy loss decreased and accuracy increased, indicating successful feature learning. With fine-tuning and data augmentation, the final model achieved a training accuracy of 74.5% and a validation accuracy of 71.2%, making it suitable for real-time classification in post-conflict zones.
The classification outputs were further grouped into high-level waste categories: recyclable, biodegradable, and non-recyclable. This logical grouping not only simplified decision-making but also enhanced the operational reliability of IoT-enabled smart bins and AR visualization modules.

B. CNN Model Training Results

The tables below show the training and validation performance of the CNN model over 10 epochs. The first table summarizes the accuracy percentages, illustrating the improvement in both training and validation accuracy as the model learns. The second table presents the corresponding loss values, highlighting the decrease in training and validation loss, which indicates better model convergence and generalization.

TABLE I. Training and Validation Accuracy

Epoch	Train Accuracy (%)	Validation Accuracy (%)
1	42.8	55.97
2	58.6	63.45
3	63.1	63.65
4	67.4	66.19
5	68.5	66.23
6	70.5	69.35
7	71.3	70.97
8	71.9	71.45
9	73.9	72.68
10	74.5	71.16

TABLE 2. Training and Validation Loss

Epoch	Train Loss	Validation Loss
1	1.77	1.29
2	1.26	1.11
3	1.11	1.08
4	1.01	1.05
5	0.97	0.99
6	0.92	0.94
7	0.88	0.91
8	0.87	0.91
9	0.81	0.86
10	0.79	0.88

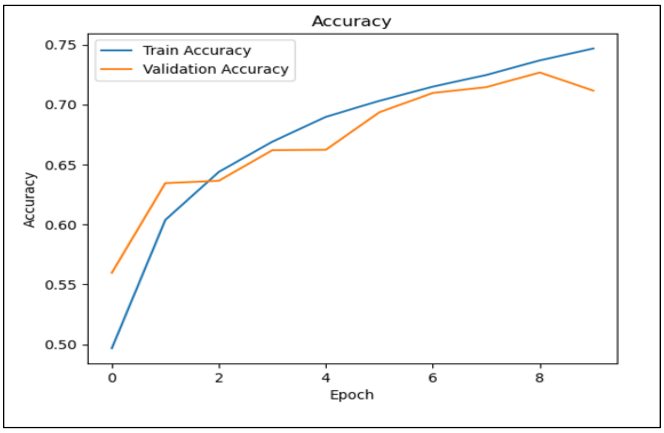

Figure 2: Accuracy Chart

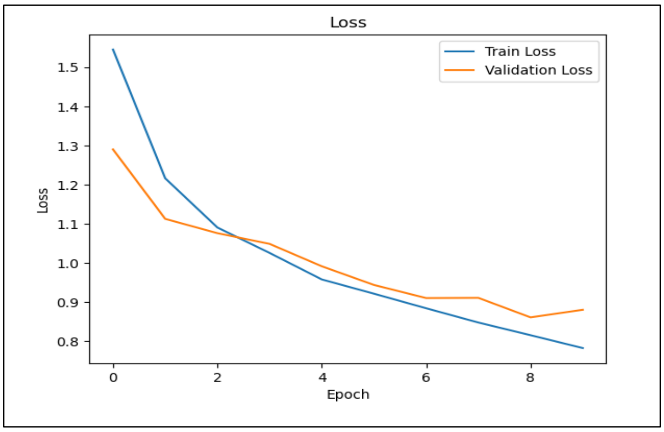

Figure 3: Loss Chart

TABLE 3. Classification Chart

Class	***Precision***	***Recall***	***F1-Score***
Plastic	*0.74*	*0.78*	*0.76*
Cardboard	*0.72*	*0.75*	*0.73*
Metal	*0.85*	*0.73*	*0.79*
Glass	*0.75*	*0.70*	*0.72*
Paper	*0.77*	*0.78*	*0.77*
Others	*0.88*	*0.85*	*0.86*
Average / Total	***0.78***	***0.76***	***0.76***

The classification report indicates a well-balanced performance across all six waste categories, with an overall precision of 0.78, recall of 0.76, and F1-score of 0.76. Among the classes, 'Others' achieved the highest F1-score (0.86), reflecting strong accuracy and consistency in predictions. 'Metal' also performed well with a precision of 0.85, although its lower recall (0.73) suggests some under-detection. In contrast, Glass' had the lowest recall (0.70), indicating more frequent missed classifications. Notably, Plastic' and 'Cardboard' showed close F1-scores (0.76 and 0.73, respectively), implying some confusion, likely due to visual similarities. Overall, the model demonstrates solid multi-class performance, suitable for AI-powered waste sorting systems, with room for further optimization.

The proposed convolutional neural network (CNN) model achieved a training accuracy of 74.5% over 10 epochs using the garbage classification dataset comprising 15,150 images across 12 household waste categories. While this performance indicates reasonable learning capability, the accuracy alone does not fully reflect the model's real-world applicability.

To better understand the performance, we include both the confusion matrix and classification report (precision, recall, F1-score), which reveal key insights. Notably, the model frequently misclassified plastic as cardboard, and glass as metal, likely due to overlapping visual textures and color similarities. This pattern of misclassification underscores the need for advanced data augmentation techniques and possibly the integration of pre-trained models (e.g., ResNet50 or EfficientNet) to improve feature extraction. Despite its current limitations, the system demonstrates potential in post-conflict scenarios or urban waste zones, where fast, automated waste classification is more critical than perfect precision.

The 74.5% training accuracy, in this context, suggests the proposed integration of AI with IoT and AR is viable and scalable.

V. Conclusion

This research presents a robust AI-driven waste classification model aimed at supporting sustainable recycling in post-conflict environments. The proposed CNN architecture trained on a diverse image dataset, integrated with IoT and AR technologies, enables intelligent, real-time waste segregation and recovery. While current accuracy levels are encouraging, future work will focus on improving generalization through transfer learning, expanding the dataset with region-specific samples, and field testing with IoT and AR systems. Achieving around 75% accuracy in the CNN model is a good starting point given the complexity of classifying waste images across 12 diverse classes. Factors such as the variability in image quality, similarities between certain waste types, and the limited number of training epochs can impact the model's performance. Additionally, the current model architecture and lack of extensive data augmentation may limit its ability to generalize well. To improve accuracy, techniques such as increasing the number of training epochs, applying more robust data augmentation, leveraging transfer learning with pre-trained networks, and fine-tuning hyperparameters can be explored. Addressing these aspects can help the model better capture the intricate features of waste images and enhance classification performance. This integrated AI-IoT-AR approach offers a scalable solution for post-conflict waste recovery and can be extended to other disaster-response and urban resilience initiatives. Its potential can be extended to broader urban resilience, smart city applications, and circular economy initiatives, making it a significant contribution to intelligent and sustainable waste management systems.

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