EnviroKen: Leveraging AI for Waste Management

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***Abstract*—Urban areas globally are brawling with the challenge of efficient waste management, a situation exacerbated in developing countries like Kenya (and other 3rd world countries) by rapid urbanisation and inadequate or or lack thereof waste disposal infrastructure. Nairobi, Kenya's capital, is at the apex this crisis, generating between 3,000 to 4,000 tons of waste daily, with a significant portion improperly disposed of in open dumpsites like Dandora, one of Africa's largest unregulated landfill sites that sprawls over 30 acres. This has led to environmental and health degradation. The study introduces EnviroKen, an innovative, AI-powered solution aimed at revolutionising waste management practices in Nairobi. EnviroKen utilizes advanced image classification and text generation models to facilitate accurate waste identification and sorting at the source, alongside providing personalised waste management recommendations. By capitalising on AI, EnviroKen purposes to enhance the efficiency of waste management processes, promote recycling and composting, and reduce the reliance on unsustainable disposal methods. This research underscores the potential of technology in addressing environmental challenges, contributing to the global pursuit of SDG 12: Responsible Consumption and Production, and offering a scalable model for urban waste management that can be adapted to similar contexts globally.**

***Index Terms*—Waste Management, AI, Kenya, Recycling, Sustainability, EnviroKen, Waste Disposal**

I. Introduction

Waste generation is set to increase from 2.24 billion tonnes in 2020 to 3.88 billion tonnes by 2050, severely impacting developing countries where improper disposal poses health and environmental risks. The high cost of effective waste management, accounting for up to 50% of municipal budgets, presents a significant challenge in creating sustainable, efficient systems [1].

A. Background

The urban landscapes, especially in developing countries like Kenya, are marred by the burgeoning crisis of waste management. Nairobi, the heart of Kenya, generates between 3,000 to 4,000 tons of waste daily, a significant challenge compounded by inadequate disposal practices and infrastructure [3]. Over 70% of this waste is organic, with the remainder comprising plastics, metals, and paper, most of which fail to reach designated disposal sites [3]. The resultant effect is the proliferation of mismanaged open dumpsites and informal landfills, exemplified by the notorious Dandora site.

This crisis not only poses severe environmental and health risks but also highlights the dire need for innovative solutions that can revolutionize waste management practices [1]. The research focuses on leveraging AI to bridge the gap between waste generation and sustainable management practices that follow the Sustainable Waste Management Act of Kenya [7].

B. Problem Statement

Nairobi, Kenya, faces an escalating waste management crisis, characterized by the daily generation of thousands of tons of waste, a substantial portion of which ends up in mismanaged dumpsites, notably the Dandora site. This crisis is compounded by the lack of efficient waste sorting and recycling mechanisms, leading to environmental degradation, public health hazards, and a missed opportunity for sustainable waste resource management. Despite various initiatives by the government and private sectors, there exists a significant gap in the adoption of innovative and scalable solutions that can effectively address the complexities of urban waste management. The urgent need for a transformative approach that leverages technological advancements to improve waste sorting, recycling, and sustainable disposal practices forms the crux of this research [2].

II. Literature Review

A. Domain of Image Waste Classification Using AI/ML/Deep Learning

Recent research, such as the study by Lei, Jiao, and Zhong [8], demonstrates the efficacy of Vision Transformers over traditional CNNs for waste classification, achieving an accuracy of 96.98% on the TrashNet dataset. This significant improvement highlights the potential of attention-based models in overcoming the limitations of CNNs, marking a pivotal advancement in waste classification accuracy [8].

Furthermore, the DeepWaste project underscores the practical application of CNNs, incorporating models like ResNet50 into a mobile app for on-device waste classification. This approach emphasizes the importance of real-time, accessible solutions for waste identification, contributing to the ease of recycling and proper waste disposal practices [9].

Additionally, the application of MobileNetV2 to waste classification addresses the balance between computational efficiency and the depth of neural network exploration. This study showcases the capability of efficient networks like MobileNet in real-world applications, such as waste sorting, which is pivotal for enhancing recycling efforts [10].

B. Domain of Smart Waste Management and Text Generation

The Trashtag challenge exemplifies the power of community engagement in waste management, further augmented by IBM Watson's AI for validating cleanup efforts. EnviroKen builds upon this foundation, integrating image classification with text generation models to provide actionable waste management recommendations, thereby extending the engagement from cleanup to preventive strategies [4].

In addressing the solid waste management scenario in India, the study on illegal dump detection using mp-CNN highlights the role of AI in localizing waste dumps with high accuracy, presenting a technological leap in managing urban waste efficiently [6].

NC State University's development of a smart waste management system, in collaboration with IBM and the National Renewable Energy Laboratory, illustrates the integration of smart sensors and AI for improved waste sorting. EnviroKen aligns with these initiatives by focusing on the upstream process of waste classification and generating educational content, aiming to empower individuals and communities towards more responsible waste handling [5].

C. Gaps and Our Contribution

While these studies demonstrate significant technological advancements, there remains a need for systems that not only classify waste but also actively engage and educate the public on sustainable waste management practices. EnviroKen aims to fill this gap by combining efficient image classification techniques with text generation models to provide personalized recommendations. This approach not only enhances the accuracy and efficiency of waste management systems but also leverages technology to promote environmental stewardship among individuals and communities.

Through this integrated approach, EnviroKen aspires to provide a comprehensive solution to waste management challenges, combining technological innovation with educational initiatives to foster a more sustainable and informed society.

III. Methodology

A. RAD Methodology

This research adopts the Rapid Application Development (RAD) methodology, emphasizing quick iterative cycles and user-centric design to integrate AI technologies into waste management systems effectively. The process involves stakeholder consultations to define project scope, user design workshops for creating an intuitive interface, and robust data preparation for AI model training.

B. Waste Image Classification Model - EnviroKen Classifier

Model Name and Details: The EnviroKen Classifier is an advanced waste classification model that employs the VGG16 architecture, a cutting-edge convolutional neural network (CNN) pre-trained on the expansive ImageNet dataset [19]. ImageNet, known for its vast array of labeled images covering a wide spectrum of objects, provides a solid foundation for feature extraction. By leveraging transfer learning, the EnviroKen Classifier harnesses VGG16's potent feature extraction capabilities, honed on ImageNet's diverse imagery [16]. During the model's fine-tuning process, the final layers of VGG16 were re-trained with our specialized waste

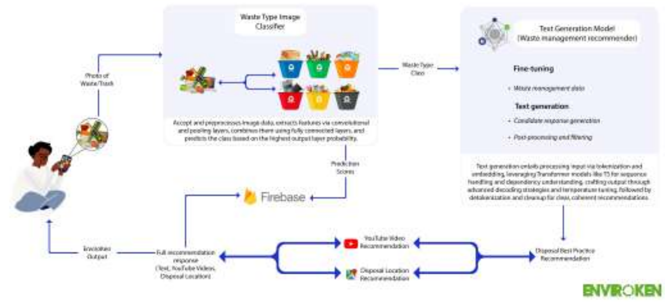

Fig. 1. EnviroKen Conceptual Framework

classification dataset, allowing the model to refine its pre-learned features for effective differentiation among various waste categories: plastic, paper, glass, metal, organic, and e-waste.

- **Name**: EnviroKen Classifier
- **Base Model**: VGG16
- **Custom Layers**:
  - Flatten Layer
  - Dense Layer with 1024 units and ReLU activation
  - Dense Layer with 512 units and ReLU activation
  - Output Dense Layer with 6 units and softmax activation (for 6 classes)
- **Optimizer**: Adam [15]
- **Loss Function**: Categorical Crossentropy

Data Used for Model: Originating from Kaggle, this dataset has been adapted to focus on six principal waste categories crucial for environmental management: e-waste, organic, glass, paper, plastic, and metal [17]. With 960 images per category, the training set comprises 5760 images in total, ensuring comprehensive exposure to various waste materials. This extensive training is supplemented by a validation set of 720 images (120 images per category) to monitor the model's performance and a test set of 720 images for the final evaluation. These datasets are pivotal in achieving the model's high accuracy in waste material identification and classification.

Data Preparation and Management: Organized into class-specific folders, the dataset's structure simplifies its integration with Keras's `ImageDataGenerator`, facilitating efficient data loading, preprocessing, and the application of real-time data augmentation techniques. This organization enhances the model's ability to generalize and perform robustly across diverse waste materials. The dataset was compiled from two primary sources on Kaggle [18] [17]:

- E-Waste Image Dataset
- Waste Classification Data

Training Details: Employing the VGG16 architecture, the EnviroKen Classifier includes 16 layers with a modification in the final fully connected (FC) layer to match the waste categories [20]. The model's training strategy involves freezing the initial 10 convolutional layers to preserve the pre-learned low-level features from ImageNet, such as edges and shapes, while the remaining layers were trained on the waste classification dataset. This approach allowed the EnviroKen Classifier to maintain the efficiency of object recognition provided by VGG16's initial layers while adapting the later layers to the nuances of waste classification. Differential learning rates were employed to ensure the integrity of pre-learned features in the frozen layers while enabling significant learning in the trainable layers, thereby fine-tuning the model to specialize in distinguishing between different types of waste materials.

C. Waste Management Text Recommendation Generator - Enviroken Text Recommender

Following the accurate categorization of waste types through our image classification model, the EnviroKen project advances its innovative approach by incorporating a text generation model. This model, based on the T5-small architecture, is renowned for its exceptional performance in natural language processing tasks [13]. It aims to provide personalized, actionable recommendations for each identified waste category, transforming classification into valuable insights for sustainable waste management.

Model Name and Details: The EnviroKen Text Recommender enhances the EnviroKen project's capabilities by generating actionable recommendations based on the classifications provided by the EnviroKen Classifier. This functionality is powered by the T5-small model, a subset of the Text-To-Text Transfer Transformer (T5) architecture designed to reframe all natural language processing (NLP) tasks into a unified text-to-text format. Unlike BERT-style models, which produce class labels or input spans, the T5-small model treats both input and output as text strings. This flexibility enables the model to handle a variety of NLP tasks with the same model architecture, loss function, and hyperparameters [13]. Developed by a team including Colin Raffel and Noam Shazeer, the T5-small model boasts 60 million parameters, making it highly effective yet efficient for diverse text generation tasks [13].

- **Name**: EnviroKen Text Recommender
- **Model Architecture**: T5-small
- **Key Features**:
  - Transformer-based encoder-decoder architecture capable of handling sequence-to-sequence tasks.
  - Unified text-to-text framework suitable for a wide range of NLP tasks.
  - Pre-trained on the Colossal Clean Crawled Corpus (C4) for robust language understanding [14].
- **Optimization Technique**: Adam [15]
- **Evaluation Metric**: Rouge scores

Data Used for Model: The dataset, purposefully curated for the EnviroKen project, supports the model in generating detailed recommendations for sustainable waste management. Comprising approximately 240 entries, it segments waste into organic and inorganic types, with further classifications for inorganic waste such as paper, plastic, metal, glass, and e-waste. This structured approach provides the T5-small model with the necessary context to generate practical and actionable advice for handling, recycling, reusing, and reducing waste [12].

Data Preparation and Management: The preparation of the dataset was meticulously executed to ensure that the model can accurately generate recommendations specific to the categorized waste types. The detailed guidelines included in the dataset facilitate the model's learning, enabling it to produce targeted advice that enhances the effectiveness of the EnviroKen project in promoting sustainable waste management practices.

Training Details: Training of the EnviroKen Text Recommender on the specialized dataset spanned 200 epochs. The process was geared towards optimizing the quality of the text output, focusing on minimizing training loss and improving Rouge score performance. This comprehensive training ensures that the model's recommendations are not only coherent and relevant but also practically applicable to waste management strategies [11].

D. YouTube Video Recommendation Feature

The YouTube Video Recommendation feature enhances user engagement by integrating with the waste image classification and text generation models. This integration facilitates the provision of video content relevant to the identified waste category and its management recommendations. For example, upon classifying electronic waste and recommending its return to the manufacturer, the system extracts keywords from the generated text to query YouTube for pertinent videos. This process aims to enrich user knowledge by visually demonstrating recommended actions, such as proper e-waste packaging and the environmental importance of electronics recycling. Currently, the feature operates on a keyword-driven basis, potentially yielding generic results.

IV. Experiment Details

A. EnviroKen Classifier Experiment Results

The training of the EnviroKen Classifier over 10 epochs showcased notable advancements in the model's ability to accurately classify waste types from the training data. However, the emergence of a disparity between the training and validation metrics underscored the challenge of overfitting, necessitating the exploration of further optimization strategies to enhance model performance.

1) Training Performance: Throughout the training phase, a pronounced reduction in training loss was observed, alongside an upward trend in training accuracy. This progression illustrates the model's growing efficiency in recognizing and classifying the training data. In contrast, validation metrics signaled a pressing need for improving the model's ability to generalize across unseen data, a crucial aspect for its practical applicability in real-world scenarios.

2) Cons: The training process unveiled significant overfitting, as evidenced by the divergent trajectories of training and validation results. Specifically, the increase of validation loss across successive epochs highlighted the model's diminishing capacity to generalize to new datasets. These findings point to the critical need for implementing strategies to curb overfitting and enhance the model's generalization capabilities.

Metrics and Visualizations: The EnviroKen Classifier's training for 10 epochs resulted in significant improvements in training accuracy and a decrease in training loss, evidencing the model's effective learning from the training data. Conversely, validation metrics painted a different picture, revealing concerns related to the model's overfitting.

Training Performance::

- **Training Loss:** Exhibited a steep decrease from 1.0550 in epoch 1 to 0.0319 by epoch 10, demonstrating the model's enhanced predictive accuracy on the training set.
- **Training Accuracy:** Improved markedly from 67.98% in the first epoch to 99.13% in the last epoch, reflecting the model's increased proficiency in classifying the training data.

Validation Performance::

- **Validation Loss:** Contrary to the training loss, validation loss exhibited a concerning upward trend, indicative of the model's struggle to generalize its learning to the validation set.
- **Validation Accuracy:** Remained considerably lower than training accuracy and displayed fluctuations throughout the training epochs, underscoring the challenge of model overfitting.

TABLE I
EPOCH SUMMARY TABLE

Epoch	Loss	Accuracy (%)	Val Loss	Val Accuracy (%)
1	1.0550	67.98	1.8517	40.71
2	0.3583	87.51	1.8228	40.00
3	0.1951	92.92	2.8477	40.00
4	0.0972	96.16	3.0287	45.00
5	0.1400	95.10	3.9830	42.86
6	0.0909	96.99	3.3908	43.57
7	0.0737	97.47	4.3258	39.29
8	0.0479	98.19	4.9353	42.86
9	0.0451	98.52	3.7407	47.86
10	0.0319	99.13	4.4020	46.43

The disparity between training and validation outcomes highlights a pronounced overfitting issue, indicating that while the model effectively learns from the training data, it struggles to apply these learnings to new, unseen data.

Enhanced Model Training with Early Stopping and Data Augmentation: A subsequent training iteration incorporated early stopping and data augmentation, aiming to bolster the model's generalization capabilities. The results, summarized in Table II, reflect the positive impact of these strategies on the model's performance.

Discussion: Our comparison of training sessions highlights the effectiveness of early stopping and data augmentation in preventing overfitting and improving model generalizability. The initial training exhibited classic signs of overfitting, with validation loss rising even as training accuracy increased. By implementing strategic modifications, the subsequent session achieved a more balanced validation loss, suggesting better model performance and reduced overfitting tendencies.

TABLE II
SUMMARY OF ENHANCED TRAINING METRICS

Epoch	Loss	Accuracy (%)	Val Loss	Val Accuracy (%)
1	1.4346	57.78	1.3087	49.44
2	0.8040	70.55	1.4232	49.86
3	0.6860	74.67	1.4737	49.03
4	0.6796	74.24	1.4550	49.58
5	0.6141	77.40	1.4070	54.58
6*	0.5866	78.25	1.4452	54.86

*Epoch at which early stopping was initiated and the model weights were restored to the best state from epoch 5.

EnviroKen Text Recommender Experiment Results

The EnviroKen Text Recommender, powered by the T5-small model, exhibited consistent performance improvements across training epochs. This is quantitatively evidenced by the progressive enhancement of Rouge scores and a steady decrease in validation loss, indicating the model's increasing proficiency in generating detailed and relevant recommendations that adhere to sustainable waste management practices.

Baseline Configuration: The initial model configuration was established with a set of fundamental hyperparameters, focusing on producing concise yet actionable advice. This configuration, though basic, laid the groundwork for the model's ability to offer practical recommendations:

- **Max Length:** 50 — This constraint ensures that responses are succinct, aiming for a maximum of 50 words to maintain brevity and relevance.
- **Num Beams:** 5 — Beam search is employed with 5 beams to refine the selection process, aiming for more precise and relevant outputs.
- **Early Stopping:** True — This feature curtails the search once all beam hypotheses conclusively reach the end token, enhancing efficiency.

Example Outputs: Educate others on the environmental impact of paper waste.

Enhanced Detail Configuration: To deepen the richness and comprehensiveness of the recommendations, the model's hyperparameters were adjusted. This refined setup aimed to facilitate the production of longer, more informative outputs that encapsulate a broader spectrum of sustainable practices:

- **Max Length:** 100 — Extended response length allows for the articulation of more detailed and informative recommendations.
- **Min Length:** 20 — A minimum length ensures that each piece of advice has sufficient depth and practical value.
- **Temperature:** 0.7 — This parameter fine-tunes the prediction randomness, fostering creativity in the generated recommendations.
- **Top_k:** 50 — Constraining word choices to the top 50 facilitates focused and relevant output.
- **Top_p:** 0.85 — Employing nucleus sampling enhances dynamic selection from the probable word pool, adding to the diversity and relevance of the text.
- **Repetition Penalty:** 1.2 — This penalty discourages word repetition, ensuring varied and engaging content.

Example Outputs: Reuse old books and magazines as decorative items or for art projects.

TABLE III
SUMMARY OF EVALUATION METRICS AT EVERY 20TH EPOCH

Epoch	Train Loss	Val Loss	R-1	R-2	R-L	Gen Len
20	0.8121	2.203	16.93	1.49	14.72	14.87
40	0.7076	2.254	18.85	1.36	15.44	14.65
60	0.6307	2.295	17.77	1.61	14.61	14.44
80	0.5779	2.341	17.04	1.59	14.63	15.34
100	0.5538	2.365	15.24	0.81	13.26	14.01
120	0.5221	2.387	14.63	0.61	13.49	14.13
140	0.5050	2.411	16.41	0.76	14.44	13.44
160	0.4922	2.432	14.93	0.47	13.07	13.20
180	0.4770	2.443	16.08	0.70	13.56	13.38
200	0.4772	2.447	16.08	0.70	13.56	13.38

Key Terms:

- **Epoch**: Complete pass through the training data.
- **Train Loss**: Model's error on training data.
- **Val Loss**: Model's error on validation data.
- **R-1 (ROUGE-1)**: Overlap of unigrams with reference texts.
- **R-2 (ROUGE-2)**: Overlap of bigrams with reference texts.
- **R-L (ROUGE-L)**: Longest common subsequence with reference.
- **Gen Len**: Average length of generated outputs.

This data indicates not only a tangible improvement in the model's ability to generate contextually rich and actionable recommendations but also highlights the effectiveness of hyperparameter tuning in refining output quality. The adjustments made for the enhanced detail configuration directly contributed to the production of more elaborate and environmentally conscious advice, underscoring the model's evolving sophistication and its potential impact on promoting sustainable waste management practices.

Hyperparameter Ablation Study: An ablation study was conducted to evaluate the impact of hyperparameter tuning on the performance of the T5-small model in generating actionable waste management recommendations. The adjustments included Max Length, Number of Beams, Temperature, and Repetition Penalty, among others. The key findings are summarized below, indicating their influence on Rouge scores and validation loss.

TABLE IV
SUMMARY OF HYPERPARAMETER ABLATION IMPACT

Hyperparam.	Rouge Δ	Val Loss Δ
Max Length $\uparrow$ (50 to 100)	+R-L	$\uparrow$
Number of Beams $\uparrow$ (2 to 5)	+R-1, +R-2	$\leftrightarrow$
Temperature $\downarrow$ (0.7)	+Diversity	$\leftrightarrow$
Sampling & Repetition Penalty $\uparrow$	+All Rouge	$\downarrow$

Legend: - $\uparrow$: Increase or improvement. - $\downarrow$: Decrease. - $\leftrightarrow$: No significant change.

This table efficiently encapsulates the essence of the ablation study, highlighting how each hyperparameter adjustment impacts the model's ability to generate detailed and relevant recommendations for sustainable waste management practices.

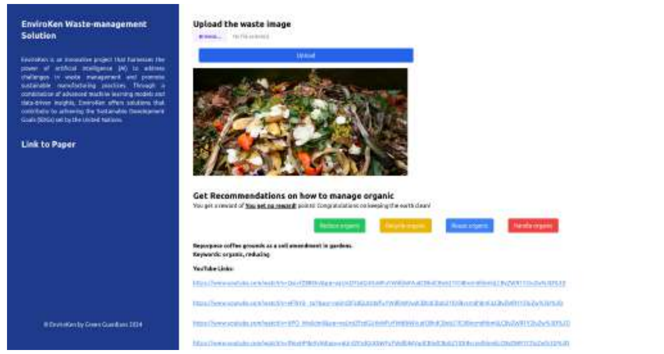

Fig. 2. EnviroKen Upload Page with video Recommendations

V. CONCLUSION AND FUTURE WORKS

EnviroKen's innovative AI solution marks a significant advancement in waste management for Kenya, with the prospect of scaling globally. The integration of image classification with text generation lies at the core of the project, which has shown great promise in identifying waste types and providing personalized recommendations for their disposal, recycling, or repurposing. As the project evolves, several enhancements are envisioned to amplify its reach and efficacy.

Future Directions and Enhancements

- **Dataset Expansion and Model Refinement:** We aim to extend the dataset and apply advanced techniques to fine-tune the AI models, thus ensuring higher precision and more nuanced waste management guidance.
- **Integration into Waste Management Systems:** Plans are underway to consider how EnviroKen can be incorporated into larger waste management infrastructures to facilitate a more systemic approach.
- **Geolocation-Based Personalization:** The application will leverage user location data to provide tailored advice on handling identified waste items, potentially guiding users to the nearest recycling centers, and designated drop-off facilities, and informing them of local collection services.
- **Incentivization through Rewards** A forthcoming strategy involves instituting a rewards system designed to enhance user engagement in sustainable waste management practices. EnviroKen anticipates motivating individuals with various incentives, potentially including Carbon Credits and vouchers, which will catalyze greater community involvement in environmental conservation.
- **YouTube Recommender System Improvements** The YouTube Video Recommendation feature constitutes a vital aspect of the user experience, and several improvements are planned:
  - Introduction of a feedback mechanism for users to rate the relevance of the videos, fostering a more tailored and dynamic recommendation engine.

– Development of performance metrics to assess the system's effectiveness in providing relevant video content, thereby informing an adaptive learning algorithm.
– Commitment to inclusivity and accessibility, with the potential addition of closed captions and multilingual support to make the educational content accessible to a diverse audience.

- **Ongoing Technical Development** Keeping the video recommendations current and relevant will be an ongoing endeavor, requiring regular review and updates to align with YouTube's content guidelines.

In conclusion, EnviroKen is dedicated to advancing a sustainable future through its AI-enabled platform. By embracing user feedback, refining its recommendation systems, and expanding its reach, EnviroKen aspires to be at the forefront of ecological education and proactive waste management, aligning with global sustainability efforts.

VI. Authors

Danroy Mwangi and **Manasseh Kinyua** are pioneering the EnviroKen project, leveraging their expertise in Environmental Science and Technology to address critical challenges in waste management through innovative AI applications. Based in Nairobi, Kenya, their collaborative efforts aim to harness the power of generative artificial intelligence for sustainable environmental solutions.

VII. Acknowledgements

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This work was made possible by the encouragement, feedback, and support from our peers, colleagues, and the broader scientific and environmental community. Their belief in the potential of AI to drive positive change in waste management has been a constant source of inspiration.

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