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Application of Convolutional Neural Network (CNN) for the Detection of Leather and Paper Waste on the Environment

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***Abstract*—** *This paper represents a significant step towards leveraging machine learning for sustainable waste management, demonstrating the potential of the technology to contribute to environmental conservation efforts with the Federal University Gashu'a as a case study. The research utilized a dataset comprising images of land environments with varying degrees of waste presence, encompassing paper and leather materials. A custom CNN architecture was designed and trained on the DeAlpha dataset, enabling the model to distinguish between these waste types. Real-time detection through webcam integration was successfully implemented, providing a dynamic solution for waste monitoring. The major findings indicated a high level of accuracy in waste detection, with the model achieving an overall accuracy of over 83%. This endeavor will address the pressing concern of environmental waste management that has become a serious menace.*

I. Introduction

Waste management has become a major global issue, impacting public health, the environment, and sustainable development (Rahman et al., 2022). Improper waste disposal leads to environmental pollution, disease transmission, and negative social and economic effects (Husni et al., 2021). Developing effective waste management systems is critical, and technology can play an important role. Waste pollution and improper disposal of materials like paper, plastics, leather, metals, and glass in land environments is a global environmental issue. According to WHO (2021), around 2 billion tons of municipal solid waste are generated worldwide each year.

While modern waste management emphasizes the "3Rs" (reduce, reuse, recycle), developing economies struggle to adopt these systems. Waste collection services only cover 44% of the urban population in low-income countries (Kaza et al., 2018). Even in advanced economies, recycling rates for municipal waste remain below 35% (OECD, 2020). This Leads to Dumping of Non-Biodegradable Wastes Outdoors.

Convolutional neural networks (CNNs) are a specialized type of deep neural network designed for processing image data (Hurst et al., 2022). CNNs consist of convolutional layers that apply a convolution operation to the input using learned filters, pooling layers that down sample the data, and fully connected layers for classification.

Flask was brought to life by Armin Ronacher in 2010, originating from an April Fool's Day joke. Despite its humorous inception, Flask rapidly gained popularity due to its simplicity, flexibility, and fine-grained control. It offers a lightweight and modular design that makes it easily adaptable to developers' needs. Flask is built on Werkzeug, a WSGI utility library, and Jinja2, a template engine, both of which provide a strong foundation for web application development.

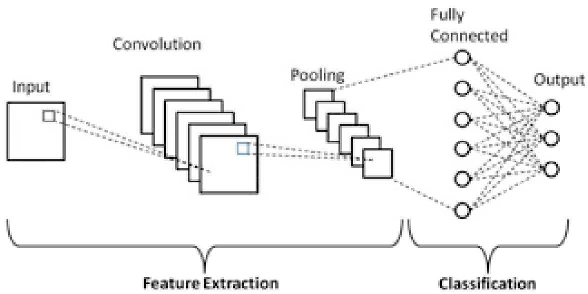

Figure 1: Generic Architecture of CNN

A number of studies have developed methods for automated waste classification using deep convolutional neural networks. (Córdova et al. 2022) compared different CNN architectures including ResNet, DenseNet, and EfficientNet for litter detection in images. They found EfficientNet-B0 achieved the best accuracy of 98.7%. (Ping et al. 2020) proposed using the Faster R-CNN model for litter detection and classification, obtaining 96.2% accuracy on a dataset of road waste images. Faster R-CNN combines a regional proposal network and convolutional network in a two-stage approach. The model was deployed on an edge computing device, enabling real-time video processing. Other research has focused on optimizing CNNs for waste classification on mobile devices or hardware with limited resources. Agbehadji et al. (2022) developed a custom 6-layer CNN optimized to run on a Raspberry Pi integrated with a smart waste bin. The model achieved 95% accuracy in classifying plastic, paper, metal, and glass objects. Modak et al. (2022) designed a compact CNN architecture called Mini-Inception to perform waste segregation on an embedded device. Testing on a public dataset showed 96% accuracy with efficient computation. 17 Object detection models like YOLO ("You Only Look Once") have also been applied for waste localization and classification. Shah & Kamat (2022) used YOLOv3 to detect different waste types in images, obtaining over 90% accuracy. YOLO models are fast and can detect multiple objects in an image. YOLOv4 is an updated

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version with improved speed and accuracy through techniques like cross-stage partial connections and a new loss function (Glenn Jocher, 2023). For waste classification, YOLOv4 could potentially detect small objects more accurately. For real-world application, some research has focused on waste classification in complex outdoor environments. Husni et al. (2021) developed a waste monitoring system using a MobileNet CNN to classify litter from footage captured by drones and surveillance cameras. The system achieved 93% accuracy in categorizing real litter like cans, bottles, and paper. Nizamuddin et al. (2022) collected a dataset of waste images from streets and tested detection models like SSD-MobileNet and RetinaNet. SSD-MobileNet achieved the top MAP metric of 61%, showing the challenges of outdoor waste detection. A common approach is integrating waste classification models with sensors and hardware systems for real-time monitoring and collection. Rahman et al. (2022) proposed an IoT-based intelligent waste management system where ultrasound sensors detect waste levels and a CNN categorizes the waste type to inform collection. Nazerdeylami et al. (2021) developed a robotic system that uses object detection and image classification to autonomously survey litter. The robot navigates to scan locations and the CNN analyzes the footage to detect and map litter. Some research has focused on detecting specific waste types relevant to different environments. Naf'an et al. (2023) optimized a CNN to identify trash types commonly found around households in Indonesia, such as plastic, paper, cloth, and metals. The model achieved 98% accuracy during field tests. Córdova et al. (2021) collected a dataset of marine litter and developed a Faster R-CNN model to detect waste objects on beaches. The approach could support collecting ocean plastics. For leather waste, Kontham and Veeramanikandasamy (2022) used pre-trained CNNs like VGG-16 and ResNet-50 to classify defective leather samples. The ResNet model achieved 18 99% accuracy on a leather defect dataset, showing potential for quality control. However, there is limited research on deep learning methods for detecting leather waste in environments. Deep CNNs demonstrate high accuracy on waste classification but can face challenges generalizing to complex real-world environments. Continued research on robust models and integrating sensors, robotics, and edge computing will enable impactful intelligent waste management systems.

II. Materials and Methods

Dataset Composition: As supervised learning techniques, CNN models require labeled datasets to train on. In this study, labeled image data of paper and leather wastes were collected and labeled from the Federal University Gashu’a waste management site and some free waste images collected from kaggle.com. The target classes are Paper waste and Leather waste. A minimum of 1000 images per class were collected, with efforts to capture objects under different orientations and lighting conditions. Data augmentation techniques like flipping, rotation and color jittering further expanded
the variability of the dataset. The collected images are labeled and splitted into training (80%) and test (20%) sets. The training set was used to optimize the CNN model parameters. The validation set monitored model performance during training and fine-tune hyper parameters. The test set provided an unbiased evaluation of the final model (DeAlpha).

Dataset Structure: The final dataset was composed of a total of 2731 images, with careful consideration given to balance, diversity, and representativeness. Approximately 30% of the images were manually collected from the Federal University Gashua waste facility, while the remaining 70% were obtained from Kaggle. *Table 1* below demonstrates how the dataset was splitted for training and testing of the model.

TABLE 1: Dataset Structure Summary

	Paper	**Leather**	**Total**
Training Set	1,182	1,094	**2,276**
Testing Set	242	213	**455**
Total	**1,424**	**1,307**	**2,731**

Model Architecture (DeAlpha): The architectural design of the CNN model wielded significant influence over its ability to discern features effectively. DeAlpha's architecture encompasses Convolutional Layers (Conv2D), Max-Pooling Layers (MaxPooling2D), Flatten Layer, Fully Connected Layers (Dense), and an Output Layer (Dense). This configuration proved to be optimal for extracting salient features from waste images

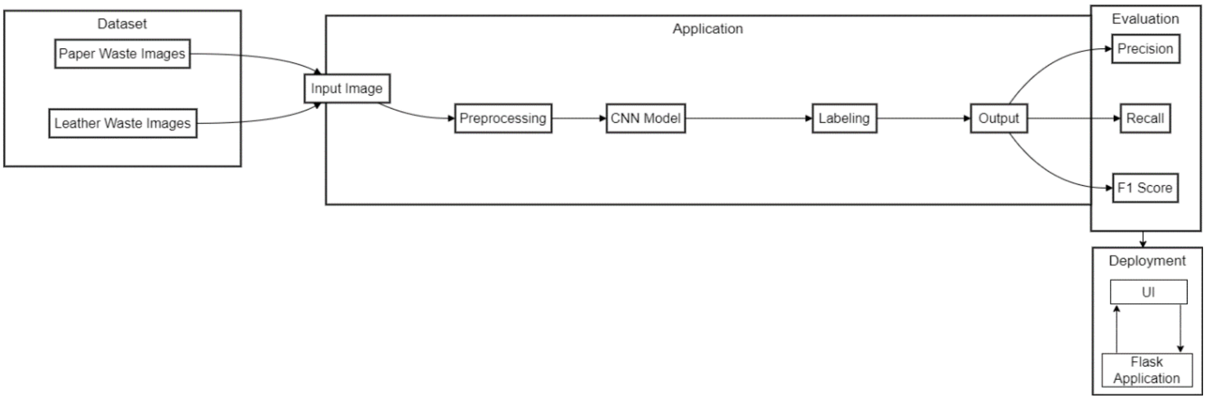

Figure 2: Overall Model Architecture (Elijah, 2023)

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Data Preprocessing and Augmentation: To prepare the data for training, data preprocessing was implemented. This involved scaling the image data to a standardized range (in this case, rescaling pixel values between 0 and 1). Furthermore, data augmentation techniques are usually applied in other to diversify the training dataset. These techniques included rotating, shifting, shearing, zooming, and flipping images. Such augmentation is instrumental in enhancing the model's ability to generalize to new, unseen data.

CNN Model: This is the major model used in this study because it has proofed to be the best in image detection amongst others. Keras with TensorFlow backend was used as the deep learning framework for implementing and training the CNN model. Key hyperparameters to tune include:

Batch Size (Images): The batch size, denoted as B, is the number of data samples processed in a single forward and backward pass through the network.

Epochs: An epoch is one complete pass through the entire training dataset. If N is the total number of training samples, then an epoch can be mathematically represented as:

$$Number\ of\ epochs = \frac{N}{B} \quad \text{[1]}$$

Learning Rate (Step Size): The learning rate, denoted as α, is a hyperparameter that scales the size of the weight updates during the optimization process. It's used in the gradient descent algorithm. The weight update rule for a single parameter w is:

$$w_{new} = w_{old} - \alpha * \frac{\delta Loss}{\delta w} \quad \text{[2]}$$

Here, $\frac{\delta Loss}{\delta w}$ is the partial derivative of the loss with respect to the weight.

Dropout Rate (units): The dropout rate, denoted as p, represents the fraction of neurons that are randomly set to zero during each training iteration. It's a probability value between 0 and 1.

Regularization (Ridge): Ridge regularization adds a penalty term to the loss function based on the L2 norm of the weights. If W represents the set of all weights in the model, the Ridge regularization term can be written as:

$$R(W) = \lambda \sum_i w_i^2 \quad \text{[3]}$$

Where λ is the regularization parameter that controls the strength of the penalty

III. Result and Discussion

Convolutional Neural Network (CNN) model developed in this study, named DeAlpha designed for detecting paper and leather wastes in the land environment. The model's performance is rigorously assessed using critical metrics including accuracy, precision, recall, and F1 score.

TABLE 2: Fine-tuning History

Iteration (n)	Batch Size (Images)	Epochs	Learning Rate (Step Size)	Dropout Rate (units)	Regularization (Ridge)	Efficiency (%)	Training Time (hrs)
1	***32***	***20***	***0.001***	***0.3***	***L2 (0.001)***	***83.03***	***1.6***
2	32	15	0.001	0.1	L2 (0.001)	79.56	1.9
3	64	25	0.001	0.5	L2 (0.001)	71.65	3.3
4	32	30	0.0005	0.4	L2 (0.001)	81.98	3.5

As seen in Table 2, out of 4 iterations; Iteration 1 with a dropout rate of 0.3 achieved the highest efficiency of 83.03%. These results give insight into how different combinations of hyper parameters affect the model's performance and training time. Depending on the specific problem and dataset, different configurations may be preferred.

TABLE 3: Used Model evaluation metrics

Metrics	Accuracy	Precision	Recall	F1 Score
Value	83.03%	53.69%	45.04%	48.99%

Deployment: The deployment strategy harnessed the power of a FLASK application coupled with a one-page website, offering user-friendly options for both image upload and real-time detection via webcam. This seamless interface was crafted with a blend of Javascript, HTML, CSS, and Python

TABLE 4: Comparison of Various Approaches with our Proposed Approach

SN	Author/Year	ML Method/Model	Dataset	Metrics
1.	Naf'an et al. (2023).	CNN and LiDAR	AlexNet	Accuracy: 80.5%
2.	Israel E. A. et al. (2022).	CNN-YOLO/Yolov3	Darknet 53.conv.74,	Accuracy: 80%
3.	Nonso N. et al. (2022).	Bespoke 5-layer CNN.	Custom.	Accuracy: 80.88%
4.	Mindy Yang et al. (2021).	SVM/CNN.	Hand collection.	Accuracy: 63%, 22%
5.	Our Proposed approach	CNN	Hybrid	Accuracy: 83.03%

Looking ahead, DeAlpha is poised for further advancements. Prospects include an expanded dataset, multi-class classification capabilities, and real-time data augmentation to bolster adaptability in diverse waste scenarios. The culmination of meticulous development and rigorous evaluation positions DeAlpha as a potent tool in the realm of waste management and environmental preservation.

IV. Conclusion

The findings of this study unequivocally demonstrate the effectiveness of the DeAlpha model in accurately identifying and classifying paper and leather waste in real-world settings. The model's ability to process and interpret visual data showcases its potential as a vital tool in waste management practices.

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