WasteNet AI: Smart Waste Classification System

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***Abstract*—Waste management is becoming a major concern amid fast urbanization and rising consumption. Manual segregation can be inefficient and even erroneous, resulting in environmental contamination. In an effort to tackle this problem, a solution has been provided by this project known as "WasteNet AI: Intelligent Waste Segregation." This project employs deep learning techniques for automation. To achieve its goal, the WasteNet model applies a pre-trained ResNet-18 with transfer learning techniques for classification into categories such as Cardboard, Glass, Metal, Paper, and Plastic. Image processing methods such as resizing and normalization also aid in increasing the efficiency and effectiveness of the proposed approach. A simple and intuitive user interface has been made available by using the Python framework known as Streamlit to enable users to upload images that predict the type of waste together with probability. Furthermore, the application offers users useful recycling tips on how best to dispose of the different kinds of waste.**

***Index Terms*—CNN, environmental Sustainability, image processing, ResNet-18, transfer learning.**

I. INTRODUCTION

Waste management systems have increasingly become critical due to urbanization and growing daily waste production. Inadequate waste separation from their sources results in pollution, ineffective waste recycling, and overload of landfills. Manual sorting of wastes is laborious and takes up lots of time while being prone to mistakes. Thus, more efficient and smart solutions are needed in this regard.

The aim of this project, which is named "WasteNet AI: Intelligent Waste Classification System," is the development of an intelligent method of classifying waste based on their photos. To reach the stated goal, deep learning and a trained ResNet-18 convolutional neural network was used, together with transfer learning. By applying deep learning techniques and transferring previously learned features, the neural network was able to classify waste into such categories as cardboard, metal, paper, glass, and plastic, while saving much time on training.

Moreover, a web-based interface implemented using Streamlit was introduced to facilitate image uploads and provide classification outputs with associated confidence scores and recycling recommendation.

II. RELATED WORK

The task of classifying waste materials has been widely explored using image processing, machine learning, and deep learning. Various methods have been developed, ranging from basic feature extraction techniques to more advanced approaches like Convolutional Neural Networks (CNNs).

Zhang et al. [1] came up with CNN-based waste material classification methodology based on image preprocessing and feature extraction techniques. The findings show that their methodology is better at classifying images than the conventional machine learning techniques. In another research work, Yang et al. [2] made the use of deep CNN techniques along with the data augmentation for improved robustness and overfitting reduction. On the other side, Olugboja and Wang [3] designed a hybrid classifier using pre-trained ResNet and SVM, showing the better result than those obtained from individual classifiers. In yet another study, Mao et al. [4] explored the use of DeepNet in waste sorting applications and emphasized the significance of reusing deep learning

On the other hand, Olugboja and Wang [3] developed a mixed model using pre-trained networks deep features in combination with SVM. Their methodology performed better than individual classifiers. In yet another study, Mao et al. [4] developed DenseNet-based methodology for waste sorting and explained how important it was to make use of deep features.

In their study, Lin et al. [5] investigated the use of the pretrained ResNet networks to demonstrate how fine-tuning could significantly to reduce the training times while achieving the high accuracy levels. The authors pointed out the importance of AI-based waste management systems and explained the constraints of manual segregation processes.

Qiao et al. [7] compared multiple deep learning frameworks, including ResNet, EfficientNet, and Vision Transformers, highlighting the advantages of deep learning algorithms in solving complex classification problems. Tan and Le [8] developed EfficientNet, an efficient network architecture capable of achieving high accuracy with fewer parameters.

Ahmad et al. [9] designed a CNN-based model embedded in smart city infrastructure to facilitate waste segregation and recycling. In another study, Li et al. [10] improved the ResNet algorithm through feature fusion methods.

Gundupalli et al. [11] discussed various smart waste management framework techniques and stressed the significance of artificial intelligence and IoT in current waste processing technologies. Rad et al. [12] used a deep-learning approaches to identify waste objects by utilizing transfer learning and attained remarkable results for benchmark datasets.

Thung and Yang [13] created a dataset for waste classification with the help of CNNs used to create a benchmark for further work in this area. Xiao et al. [14] developed a light-weight CNN for performing classification on a mobile device.

The recent works by Aral et al. [15] emphasized the potential of deep learning methods in sustainable waste management. Thus, from the above discussion, it says that the application of deep learning algorithms, in particular, CNN and transfer learning, leads to significant improvements in waste classification accuracy in comparison with conventional methods.

III. PROBLEM STATEMENT

Efficient waste segregation remains a significant challenge in today's waste management systems, contributing to environmental degradation and reduced recycling efficiency. Traditional waste sorting methods rely heavily on manual effort, making the process slow, labor-intensive, and susceptible to human mistakes. Misclassification of materials such as plastic, paper, metal, glass, and cardboard further limits the effectiveness of recycling and leads to increased waste accumulation in landfills. Moreover, the absence of accessible and user-friendly technological solutions reduces public participation in proper waste disposal practices. Hence, there is a growing need for a smart and automated system that can accurately identify different types of waste and support individuals in making environmentally responsible disposal choices.

IV. PROPOSED METHODOLOGY

The proposed methodology of the suggested approach will reflect the complete workflow involved in waste classification through deep learning approaches. The system architecture reflects how input is taken in, converted, and then it passes through the various steps within the model to ensure accurate predictions. The architecture of this system has been designed in such a way as to ensure efficiency and scalability of the process. Below are the layers of this architecture.

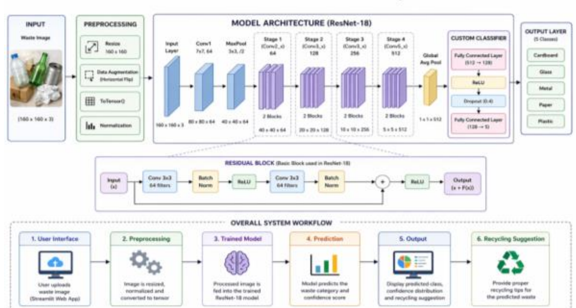

Figure 1: System Architecture

A. Input Layer

Input to the model is acquired in the form of images of the waste by the user. In most cases, the input will be composed of elements such as plastics, glass, cardboard, or papers.

B. Pre-processing Layer

In this stage, the input image is reduced to size (160×160). It is further transformed into the tensor form and normalized using predefined values. The image can be horizontally flipped for improved generalization purposes.

C. First Convolutional Layer (First Stage Feature Extraction)
The input is then run through the initial Convolutional Layer (Conv1) where fundamental features such as edges and textures are extracted from the different input image. Afterwards, the max pooling layer that helps to reduce the image size to conserve computational resources.

D. Residual Blocks (Feature Extraction)
The model consists of different stages of residual blocks. Each block has skip connections designed to eradicate gradient vanishing problem during training sessions.

E. Global Average Pooling Layer
Following feature extraction is reducing the feature maps with help of global average pooling. This step is needed to reduce the number of parameters involved. It also makes it ready for further classification.

F. Fully Connected Layer (Classifier)
After extracting the features from this input image is passing it to a fully connected dense layer. The activation functions include ReLU, along with dropout. The last layer makes predictions on the five waste classes.

G. Output Layer
This layer is responsible for generating the probabilities for each of the classes. For that, the output layer uses the Softmax function. The maximum class probability will be selected as the prediction.

H. End-to-end process (System workflow)
The entire process includes combining the model with a Streamlit application interface. The user uploads an image file, which is processed in each of the layers in the CNN model.

IV. IMPLEMENTATION

A. Environment Setup
In this implementation, an environment is set up by initializing the necessary tools such as Python and PyTorch, Torchvision, Streamlit, NumPy, and Pandas. If GPU support exists, it will be selected as the computing device for the process, and training and deployment will continue.

B. Dataset Preparation
For the waste image dataset, different folders are created for cardboard, glass, metal, paper, and plastic. These images can be loaded using the ImageFolder function, where the labeling will be done automatically. They can then be partitioned into training and validation datasets.

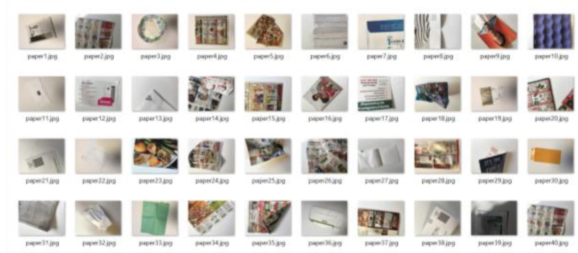

Figure 2: Dataset images

Figure 2 illustrates pictures from the data set utilized in the current study. The total number of pictures in this dataset is equal to 2,390, and these pictures have classified into five different categories, which comprise cardboard (403 images), glass (501 images), metal (410 images), paper (594 images), and plastic (482 images). Moreover, each class is stored in its folder; therefore, the ImageFolder method can be used for automatically labelling data. Different backgrounds, lighting, and orientations are present in the dataset that will help the model to learn generalizable features. All images undergo resizing and normalisation before training.

C. Data Preprocessing
Data preprocessing involves applying transformations to each image, including operations such as resizing, normalisation, and converting to tensor. Data augmentation is employed to enhance the model's ability to learn from diverse variations in the data.

D. Model Selection and Fine-Tuning
A pre-trained ResNet-18 network is selected for the feature extraction stage, where all its layers are frozen to keep learned features, whereas only the last fully-connected layer is fine-tuned according to the amount of waste classes. Thus, transfer learning technology will be applied to shorten the training period and achieve higher accuracy.

E. Model Training
During model training stage, training data is optimized to train the model with a loss function and Adam

optimizer. A specified number of training epochs is defined during the training phase.

F. Model Evaluation and Saving
After training this model, evaluation phase starts using the validation dataset, where the model attains the highest level of accuracy among others, and is saved in a .pth file for further use.

G. Deploying the Model
This trained model is then deployed in a Streamlit web application. The system goes into testing mode to maintain consistency while predicting. This makes the model suitable for real-time implementation and practical use.

H. Interaction with Users and Predicting
Through the web portal, a user is able to upload image which undergoes pre-processing and is sent to model for prediction. The model gives out predictions regarding the waste category along with confidence levels using softmax function.

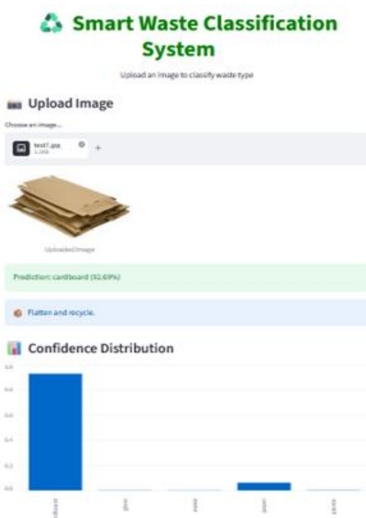

Figure 3: Application Interface Output

The result of the Smart Waste Classification System is shown below in Figure 3 via the Streamlit web application. For the system to function effectively, classify the category of waste in an uploaded picture and give its confidence value, the user simply needs to upload an image of the waste to the web application, which also gives out a confidence distribution plot and a recycling recommendation.

V. RESULTS AND DISCUSSION

Performance-wise, the developed system proves to be efficient for classifying images of wastes utilizing a machine learning-based system. The classifier can classify the various types of wastes effectively with a considerable degree of reliability in real-time. Furthermore, the incorporation of a user interface improves the effectiveness of the developed system since interaction and visualization become possible.

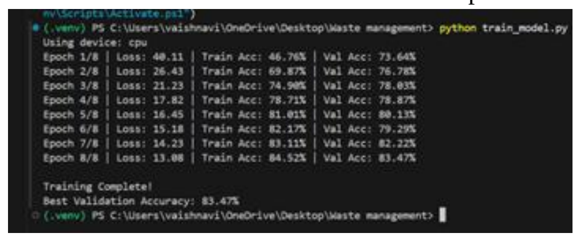

Figure 4: Accuracy of validation

Figure 4 depicts the process of the training phase, as well as training and validation accuracy and loss throughout the process of learning. It is seen that the model experiences a consistent reduction of training losses while training and validation accuracies increase over time, thus proving proper training. Moreover, the achieved best validation accuracy reaches 83.47%.

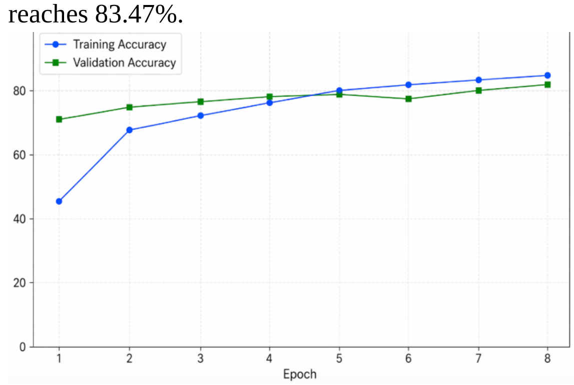

Figure 5: Training vs Validation Accuracy

The Figure 5 illustrates the comparison between training and validation accuracy across epochs. It can be seen clearly that the training accuracy increases steadily as the model learns from the dataset, while the validation accuracy also shows a consistent improvement with minor fluctuations. This trend indicates that the model is learning effectively and generalizing well without significant overfitting.

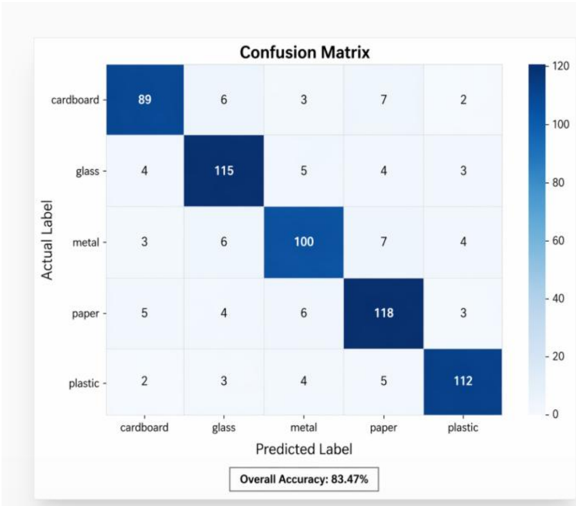

Figure 6: Confusion Matrix

Figure 6 illustrates confusion matrix which shows the importance of the classification model, which is based on comparison between the true label and the predicted label of given image belonging to each type of waste. As shown in the matrix, most of the predictions are located on the diagonal, meaning that the classification model predicts the majority of the images without any significant errors, where only small errors may exist due to similar types of waste being present in the prediction.

VI. CONCLUSION AND FUTURE ENHANCEMENTS

The WasteNet AI: Smart Waste Classification System demonstrates how deep-learning models can be used effectively in waste classification problems. By leveraging pre-trained ResNet-18 models for transfer learning, the system proves capable of achieving accurate results without the need for excessive training time and high computational power. Through the implementation of a Streamlit-based interface, the prediction process becomes more intuitive, leading to greater practicality in day-to-day activities.

To improve performance, it is possible to work on expanding the data set's size and diversity, which will contribute to the overall increase of accuracy. It is worth considering the possibility of fine-tuning the model's deeper layers or even using a deeper model altogether. One may consider working with real-time video stream data. Furthermore, this system can be used to automatically segregate waste with help of smart bins.

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