GREEN-SORT: DEEP LEARNING ALGORITHM FOR WASTE CLASSIFICATION

1st Pradul O P
dept.Artificial Intelligence and Data Science
Jyothi Engineering College
Thrissur, India
pradul2002@gmail.com

2nd Avanthika P U
dept.Artificial Intelligence and Data Science
Jyothi Engineering College
Thrissur, India
avanthikapu@gmail.com

3rd Alphin C J
dept.Artificial Intelligence and Data Science
Jyothi Engineering College
Thrissur, India
alphincj123@gmail.com

***Abstract*—Waste classification using deep learning involves applying advanced neural networks to automatically categorize and classify different types of waste materials based on their visual features. By training Deep learning models, such as convolutional neural networks (CNNs), on a large dataset of waste images, the models learn to recognize patterns and characteristics associated with specific waste categories. These models extract meaningful visual features from waste images, enabling them to differentiate between recyclable and non-recyclable materials, hazardous waste, organic waste, and more. Once trained, the models can be deployed to classify waste items in real-time, guiding waste management processes like sorting and recycling by automating the identification and segregation of waste materials. Waste classification using deep learning improves waste management efficiency reduces human error, and promotes recycling efforts. It enables the development of smart waste management systems that enhance waste sorting accuracy and contribute to a more sustainable and environmentally conscious approach to waste disposal.**

***Index Terms*—Waste Classification, Deep Learning Models, Visual Features, Recyclable Materials, Hazardous Waste, Organic Waste, Real-Time Classification, Automation, Waste Management Efficiency, Smart Waste Management Systems, Sustainability**

I. INTRODUCTION

Waste management is a critical global challenge, and effective waste classification is essential for implementing sustainable waste disposal strategies. Traditional waste classification methods rely heavily on manual inspection, which is time-consuming, labor-intensive, and subject to human error. With the advancements in machine learning and computer vision, there is an opportunity to develop an automated waste classification systems that can improve the efficiency and accuracy of waste sorting processes. A waste classification system using a machine learning techniques offer a promising solution to automate the waste categorization process. By leveraging the power of machine learning algorithms, this system can analyze the visual characteristics of waste materials and classify them into predefined waste classes. The objective is to accurately identify different types of waste, such as plastic, paper, glass, metal, and organic waste, based on their visual attributes. The proposed system consists of several stages, starting with data collection. A diverse dataset of waste images needs to be compiled, covering a wide range of waste types and variations. This dataset will serve as the foundation for training the machine learning model. Feature extraction plays a crucial role in the waste classification system. State-of-the-art techniques, such as convolutional neural networks (CNNs), are used to extract meaningful and discriminative features from the waste images. CNNs are well-suited for image analysis tasks, as they can learn hierarchical representations of visual data, capturing both low-level features like edges and textures, as well as high-level semantic information.

II. RELATED WORKS

The system for classifying waste intelligently improves the An effective waste management system is required due to the growing concern over the accumulation of solid waste in urban areas. We suggest utilizing a Support Vector Machine (SVM) and Residual Neural Network (ResNet-50) to create an intelligent waste material classification system. Using the Thung and Yang dataset, this system obtains an accuracy of 87% in classifying waste categories, such as glass, metal, paper, plastic, etc. Waste separation gets quicker, more intelligent, and incorporates human interaction with the use of this technology. In addition to addressing the health and environmental risks connected to inappropriate waste disposal, it streamlines the procedure.

In order to address the crucial problem of garbage management, this study suggests a mobile application for effective garbage classification and data entry into a Google Spreadsheet database. After improving with a genetic algorithm, we achieved an astounding 99.6% accuracy using 10,108 photos using the densenet121 deep learning platform. The final model was modified for usage in mobile applications, obtaining GPS location, garbage type, and detection accuracy. In the last test, the program demonstrated quick data transfer in 0.86 seconds, offering a useful trash management approach.

A study suggests an automatic waste categorization and sorting system that consists of two stages: Waste Recognition. Whereas the Recognition-Retrieval Model divides trash into four categories, the Recognition Model divides waste into thirteen subcategories. For comparison, a one-stage classification model is trained. Ten people sort the data manually, and the top-performing models are tested on an automated sorting device. The Recognition-Retrieval Model's average accuracy (94.71% ± 1.69) is found to be much greater than that of the Classification Model (69.66% ± 3.43) and manual sorting (72.50% ± 11.37), according to the results.

III. METHODOLOGY

A. Dataset

The dataset consists of 6 classes – Electronic waste, Food waste, Glass, and Paper. The project utilizes a dataset comprising images from "Waste Classification PI," "Waste Classification Dataset," and "Food-101 Dataset" with six waste classes. Low-quality photos from specific classes were included in some datasets. The image sets with the greatest quality and image count were included in the final dataset.

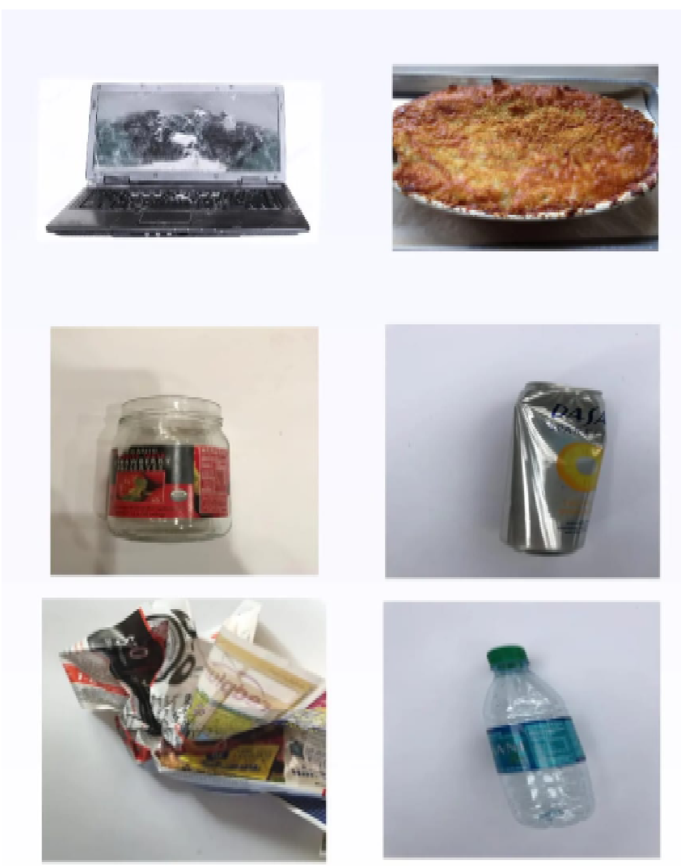

Fig. 1. Types of Waste

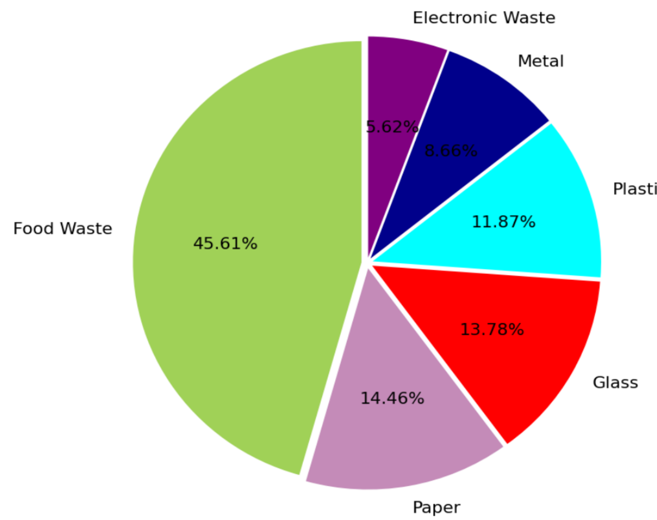

Fig. 2. Classwise Distribution

B. Data Preprocessing

Enhancing the data's quality and adapting it to the particular data mining task is the aim of data preparation. Rescaling the input photos is a crucial step in the data preprocessing process. During training, the normalization method enhances convergence and guarantees consistent ranges. The use of data augmentation techniques improves the robustness and generalization capacities of the model.

C. Data Collection Procedure

To initiate the data-gathering process, establishing waste categories like plastic, paper, glass, metal, and organic trash is essential. A diverse dataset of waste photos is then compiled, and sourced from cameras, the internet, or existing databases. Ensuring a sufficient number of photos per waste type is crucial for effective training. Subsequently, each image undergoes manual labeling or annotation, with the option of utilizing crowdsourcing platforms or annotation technologies. Finally, the dataset is partitioned for training and validation purposes.

D. Data Augmentation

Techniques for data augmentation were used to expand the quantity and variety of the dataset. For this, the Keras ImageDataGenerator class was used. enhancement Among the augmentation techniques were zoom, horizontal flips, rotation, and shifts in both directions. For every original image, many augmented images were produced, creating a larger and more diverse dataset.

E. Data Splitting

A training set and a testing set were created from the preprocessed and enhanced dataset. The model was trained on the training set, and its performance was assessed on the testing set. In order to evaluate the model's capacity to generalize to previously unviewed data, this split was carried out. A subset of the dataset was randomly chosen for the testing set at the split, and the remaining data comprised the training set.

F. Architecture Diagram

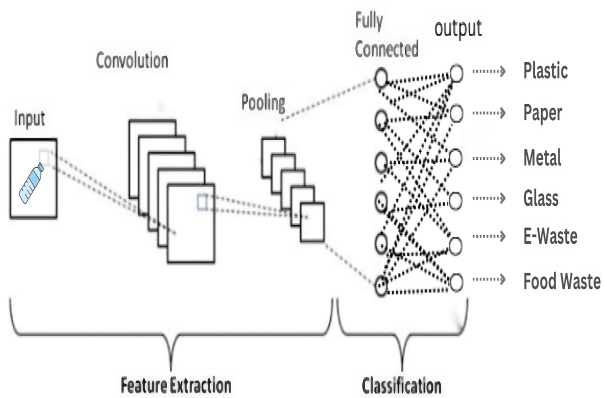

Fig. 3. Architecture Diagram

The Convolutional Neural Network (CNN) architecture is commonly used for image classification tasks. The model, consisting of six convolutional layers and five maximum loading layers, extracts features from the input images through filters of different sizes, denoted by (3, 3), and the number of filters increases as the network deepens. Rectified Linear Unit (ReLU) acts as an activation function in convolutional layers, correcting non-linearity and capturing complex patterns. After each convolutional layer, maximum collection layers sample the feature maps by selecting the maximum value within a specified window size, reducing spatial dimensions, and extracting important features. The smoothed layer transforms the 3D feature maps into a 1D vector by combining the convolutional block with fully connected layers that fulfill the final predictions. The fully connected layers include a dense layer with 512 units and ReLU activation, followed by a dropout layer with the removal of 0.5, which reduces overfit by randomly turning off units during training. An output layer with six units and a softmax activation function ensures that the predicted probabilities sum to 1 in a multiclass classification. The model is built using the Adam optimization tool, which uses a learning rate of 0.001 and uses categorical cross entropy as a loss function suitable for such tasks, while accuracy is the evaluation metric. This CNN model integrates multiple convolutional and pooling layers to extract hierarchical features, aiming to learn discriminative features and generate accurate predictions for image classification tasks.

IV. IMPLEMENTATION DETAILS AND RESULTS

This project utilizes deep learning techniques, specifically Convolutional Neural Networks (CNN), to automate and enhance the waste sorting process. The model is trained over 82 epochs, with a batch size of 32, using pre-processed and augmented data. The model architecture comprises convolutional layers with a 3x3 filter size, employing 32, 64, 128, 256, and 512 filters successively. MaxPooling2D layers with a 2x2 size are integrated to downsample the feature maps. For training, the Adam optimizer is utilized. The choice of Categorical Cross Entropy as the loss function aligns with the model's classification task. These specifications form a robust convolutional neural network configuration, conducive to effective feature extraction and classification during the training process.
The training involves iterating through the entire dataset, and the model's performance is continually evaluated on both the training and validation sets to monitor progress and prevent overfitting. Implemented in Keras, the project employs data generators for efficient batch loading and preprocessing. The trained model achieves a notable training accuracy of 91.59% and a validation accuracy of 92.32%. The project outlines the methodology, including dataset collection, preprocessing, model construction, and training, emphasizing the real-world applications in waste sorting facilities and recycling centers. Tools for data analysis and Python programming, such as PyCharm, Python 3, Google Colab, Tkinter, and Jupyter Notebook, are used. These specifications provide ecosystem diversity and compatibility for cooperative development and analysis efforts.

Continuous monitoring and periodic retraining are underscored for adaptability and sustained effectiveness, contributing to improved waste management practices and environmental sustainability.
Presenting the results of the experiments. The performance metrics used are,

- Accuracy and Loss
- Precision, Recall, F1 score, Support
- Confusion Matrix

A. Accuracy And Loss

After training the model for 82 cycles, the model achieved a training loss of 0.2291 and a training accuracy of 91.59%. The validation loss at the end of training was 0.2682, with a validation accuracy of 92.32%. These metrics show that the model performed well during training, achieving high accuracy and relatively low loss in both the training and test sets. This shows that the model generalizes well to unseen data as it maintains high accuracy and reasonable loss on the test set. Models show strong performance inaccuracy and high levels of accuracy were achieved both during training and evaluation of test data. The loss values indicate that the mode effectively minimizes the difference between the predicted and the actual class probabilities, further supporting its reliability in classification tasks. The model shows strong performance with an accuracy of and high accuracy in both training and test data evaluation. The loss values show that the model effectively reduces the difference between predicted and true class probabilities, further supporting its reliability in classification tasks.

Figure 3.4: Model Accuracy

Figure 3.5: Model Loss

B. *Precision, Recall, F1 Score,Support*

The following metrics are displayed in the classification report that is generated.

- Accuracy: With precision, the percentage of accurately identified positive cases (true positives) from all of the cases that were projected to be positive. Recall, which is often referred to as sensitivity or true positive rate, quantifies the percentage of accurately anticipated positive cases among all actual positive cases.
- F1 score: This balanced indicator of the model's performance is calculated as the harmonic mean of precision and recall
- Support: The number of instances in every class is represented by support. It gives insight into how the classes in the dataset are distributed. The model performs well overall in terms of precision, recall, and F1 score measures, indicating that it is capable of accurately identifying the various classes.

C. *Confusion Matrix*

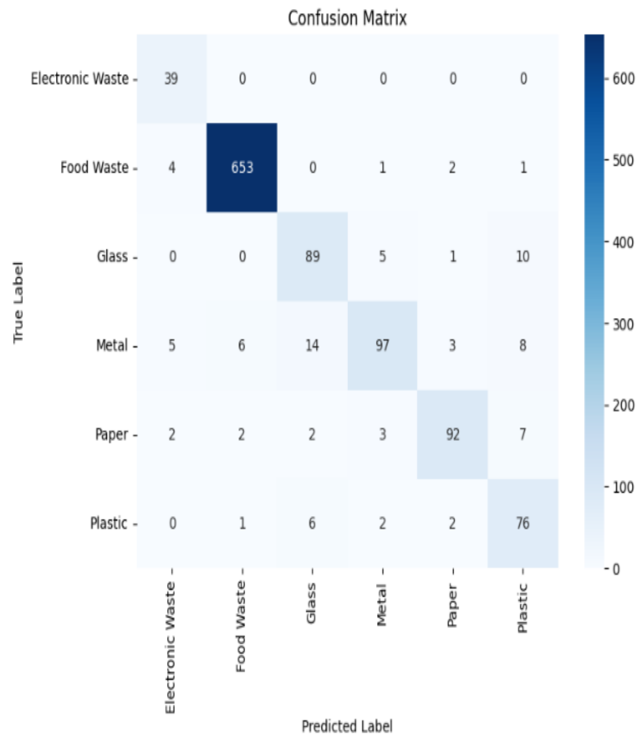

Fig. 4. Confusion Matrix

The Confusion Matrix is generated to visualize the model's performance in classifying the test dataset. The test dataset is imbalanced, hence there are differences in the number of test images in each class.

D. *Evaluation Metrices*

We used a variety of common performance criteria to evaluate the deep learning models' prediction abilities. These measurements were F1 score, recall, accuracy, and precision. Precision estimates the percentage of accurately detected positive cases among all positive forecasts, whereas accuracy assesses the total correctness of the model's predictions. Recall, which is often referred to as sensitivity, quantifies the percentage of accurately recognized positive cases out of all real positive cases. The F1 score takes into account both false positives and false negatives, offering a measure that strikes a compromise between precision and recall. We obtain a thorough grasp of the models' performance by assessing them with these metrics. Where TP (true positives) is the number of correctly classified images (i.e., for each one of the classes),

$$Precision = \frac{TP}{TP + FP} \quad \text{-(1)}$$

$$Recall = \frac{TP}{TP + FN} \quad \text{-(2)}$$

$$F1 = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad \text{-(3)}$$

$$Accuracy = \frac{\sum_{i}^{No.\ of\ Classes} TP_i}{No.\ of\ testing\ images} \quad \text{-(4)}$$

Fig. 5. Evaluation Matrix

FP (false positives) is the number of wrongly classified images as another class, and FN (false by the classifier).

Class	Precision	Recall	F1-Score	Support
Electronic Waste	0.78	1.00	0.88	39
Food Waste	0.99	0.99	0.99	661
Glass Waste	0.80	0.85	0.82	105
Metal Waste	0.90	0.73	0.80	133
Paper Waste	0.92	0.85	0.88	108
Plastic Waste	0.75	0.87	0.80	87
Average	0.86	0.88	0.87	1133

Fig. 6. Evaluation Matrix

E. User Interface

Fig. 7. Home Page

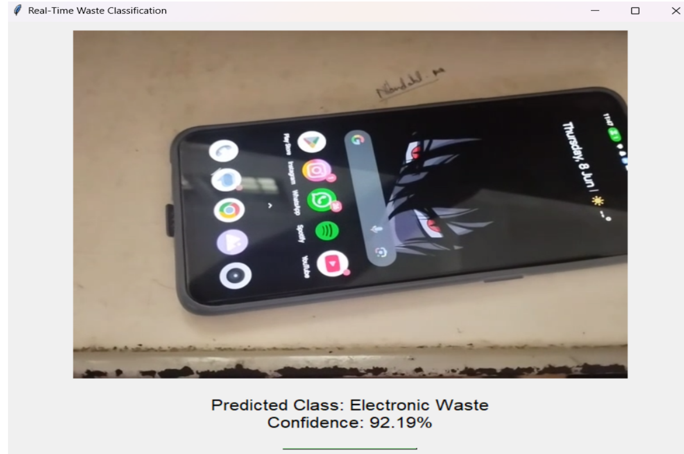

Fig. 8. Result Page

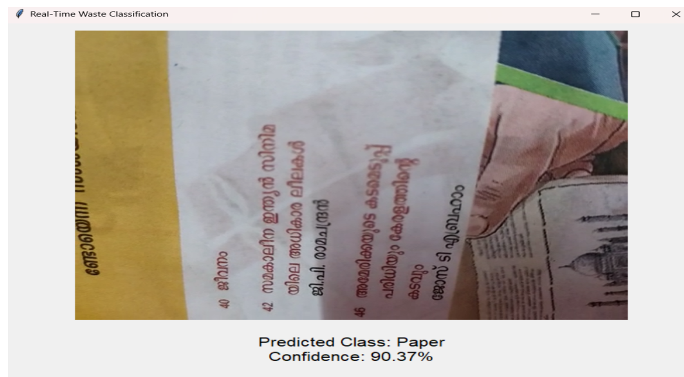

Fig. 9. Result Page

V. CONCLUSION

The overall aim of our topic is to classify waste materials according to their types and also thereby reducing pollution. This deep learning technique is used to classify different types of waste material, like paper, glass, metal, food, plastic, and electronic wastes. Deep learning models demonstrate strong performance in accurately categorizing different types of waste, enabling automated sorting processes and reducing human error. The application of deep learning allows for processing large volumes of waste data and learning complex patterns without the need for manual feature engineering. Future advancements in this field hold the potential for improving classification accuracy, handling rare waste classes, and incorporating multi-modal data sources. Real-time waste classification systems and large-scale monitoring provide valuable insights for waste management strategies. The future scope of waste classification through deep learning holds promising opportunities, emphasizing hyperparameter tuning for optimal model performance, addressing class imbalances using techniques like oversampling (e.g., SMOTE) or undersampling (e.g., RandomUnderSampler), and exploring diverse

CNN architectures, including advanced models like ResNet or CNNs with attention mechanisms. These strategies aim to refine waste classification accuracy and enhance sustainable waste management practices.

VI. Acknowledgment

We sincerely thank all contributors for their support in making our project successful. Special appreciation to God for guidance. Gratitude to Jyothi Engineering College Management, Dr. Jose P Therattil, and Mr. Bineesh M. Thanks to Dr. Seenia Francis, Ms. Parvathy Jyothi, and all staff for their unwavering support. Finally, heartfelt thanks to our parents and friends for their love and inspiration.

References

[1] O. Adedeji and Z. Wang, “Intelligent waste classification system using deep learning convolutional neural network,” Procedia Manufacturing, vol. 35, pp. 607–612, 2019.

[2] H. I. K. Fathurrahman, A. Ma’arif, and L.-Y. Chin, “The development of real-time mobile garbage detection using deep learning,” Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI), vol. 7, no. 3, p. 472, 2022.

[3] S. Zhang, Y. Chen, Z. Yang, and H. Gong, “Computer vision-based two-stage waste recognition-retrieval algorithm for waste classification,” Resources, Conservation and Recycling, vol. 169, p. 105543, 2021.

[4] N. Ramsurrun, G. Suddul, S. Armoogum, and R. Foogooa, “Recyclable waste classification using computer vision and deep learning,” in 2021 Zooming Innovation in Consumer Technologies Conference (ZINC), pp. 11–15, IEEE, 2021.

[5] D. Ziouzios, N. Baras, V. Balafas, M. Dasygenis, and A. Stimoniaris, “Intelligent and real-time detection and classification algorithm for recycled materials using convolutional neural networks,” Recycling, vol. 7, no. 1, p. 9, 2022.

[6] Z. B. Razali and G. Madasamy, “An application of image processing for automated mixed household waste sorting system,” in International Conference on Man-Machine System (ICoMMS2012), Penang, vol. 27, pp. 28–32, 2012.

[7] M. M. Russel, M. Chowdhury, M. Uddin, A. Newaz, and M. M. M. Talukder, “Development of automatic smart waste sorter machine,” 11 2013.

[8] K. Tarun, K. Sreelakshmi, and K. Peeyush, “Segregation of plastic and non-plastic waste using convolutional neural network,” in IOP Conference Series: Materials Science and Engineering, vol. 561, p. 012113, IOP Publishing, 2019.

[9] Y. Liu, K.-C. Fung, W. Ding, H. Guo, T. Qu, and C. Xiao, “Novel smart waste sorting system based on image processing algorithms: Surf-bow and multiclass svm.,” Comput. Inf. Sci., vol. 11, no. 3, pp. 35– 49, 2018.

[10] J. Bobulski and M. Kubanek, “Deep learning for plastic waste classification system,” Applied Computational Intelligence and Soft Computing, vol. 2021, pp. 1–7, 2021.

[11] F. A. Azis, H. Suhaimi, and E. Abas, “Waste classification using convolutional neural network,” pp. 9–13, 2020.

[12] “Waste classification dataset,” *Kaggle*, https://www.kaggle.com/datasets/shubhamdivakar/waste-classification-dataset.

[13] “Food-101,”https://data.vision.ee.ethz.ch/cvl/datasets_extra/food-101/.

[14] “Waste classification pi,”https://www.kaggle.com/datasets/alveddian/wasteclassification-data.

[15] Q. Hu, L. Ma, and J. Zhao, “Deepgraph: A pycharm tool for visualizing and understanding deep learning models,” in 2018 25th Asia-Pacific Software Engineering Conference (APSEC), pp. 628–632, IEEE, 2018.