Project Report

“GREEN-SORT:DEEP LEARNING ALGORITHM FOR WASTE CLASSIFICATION”

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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.

1. 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 automated waste classification systems that can improve the efficiency and accuracy of waste sorting processes.

A waste classification system using machine learning techniques offers 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.

The performance of the waste classification system can be evaluated using standard metrics like precision, recall, and F1 score. These metrics measure the accuracy and effectiveness of the system in correctly identifying waste materials and assigning them to the appropriate waste classes.

In this study, we aim to develop an automated waste classification system using machine learning techniques. By combining computer vision, machine learning algorithms, and waste management principles, we strive to enhance waste-sorting processes, promote sustainability, and contribute to a cleaner and greener environment.

1.1 PROBLEM STATEMENT

The management and disposal of waste have become significant environmental challenges in today's world. Effective waste classification is a crucial step towards proper waste management and recycling processes. Manual waste sorting is time-consuming, error-prone, and resource-intensive. Leveraging the power of technology, this project aims to develop an automated waste classification system using AI and machine learning techniques. The primary objective of this project is to create a robust model that can accurately classify different types of waste materials into predefined categories. The model should be able to analyze images of waste items and assign them to appropriate classes such as plastics, paper, glass, organic, and metal, among others.

1.2 Motivation

→ Real-time processing: The system can quickly process images,making it ideal for waste-sorting plants or public spaces where fast decisions are necessary.

→ Easy to use: The system is easy to use and does not require any special training or skills.

→ Reduce: It reduces environmental pollution, improves waste management efficiency, and increases the recovery and reuse of valuable resources.

1.3 OBJECTIVES

The main objectives of this project are as follows:

1. The Deep Learning model aims to accurately predict the type of waste, facilitating proper waste classification. When successful in predicting the waste type, the system will display both the waste type and the corresponding waste category, enabling effective waste management

2. If the system accurately predicts the type of waste, the model will display the waste type and the respective category the waste belongs to

3. However, if the system fails to identify the waste type, the model will not display the waste category, and thereby we cannot get the proper identification and their class.

1.4 SIGNIFICANCE OF THE PROJECT

The significance of a waste classification model powered by artificial intelligence (AI) is far-reaching and impactful, contributing to various aspects of environmental sustainability, waste management efficiency, and resource conservation. In conclusion, an AI-based waste classification model has the potential to revolutionize waste management practices, promote sustainability, and contribute to a cleaner and healthier environment for current and future generations.

2. LITERATURE REVIEW

2.1 PAPERS & REVIEW

The findings highlight its potential for automating and improving waste management processes. Various techniques such as CNNs and RNNs have been explored for accurate classification of waste materials. Image-based classification using CNNs has shown promising results in identifying waste objects, while text-based classification techniques using natural language processing have been used to categorize waste based on textual descriptions. Multimodal fusion approaches combining image and text data have been investigated for improved accuracy. Transfer learning with pre-trained models like ResNet, VGGNet, and BERT has been adopted for leveraging existing knowledge. Data augmentation and ensemble methods have been used to overcome data limitations and enhance classification performance. The survey provides valuable insights into the advancements, challenges, and potential

2.1.1 . Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network

We propose an intelligent waste material classification system using Residual Neural Network(ResNet-50) and Support Vector

Machine(SVM). This system achieves 87% accuracy in classifying waste types (glass, metal, paper, plastic, etc.) using the Thung and Yang dataset. By implementing this system, waste separation becomes faster, more intelligent, and involves human participation. It simplifies the process and addresses environmental and health hazards associated with improper waste management.

2.1.2 P The Development of Real-Time Mobile Garbage Detection Using Deep Learning

This study proposes a mobile application for efficient garbage classification and data entry into a Google Spreadsheet database, addressing the critical issue of garbage management. Utilizing 10,108 images and the densenet121 deep learning platform, we achieved an impressive 99.6% accuracy after optimizing with a genetic algorithm. The resulting model was converted for mobile application use, capturing garbage type, detection accuracy, and GPS location. In the final experiment, the application showcased rapid data transmission within 0.86 seconds, providing an effective solution for garbage management

2.1.3 Computer Vision Based Two-stage Waste Recognition-Retrieval Algorithm for Waste Classification

This study proposes a two-stage Waste Recognition-Retrieval algorithm for automatic waste classification and sorting. The Recognition Model recognizes waste into thirteen subcategories, while the Recognition-Retrieval Model classifies them into four categories. A one-stage Classification Model is trained for comparison. The best-performing models are tested on an automatic sorting machine, while manual sorting is performed by ten participants. Results indicate that the average accuracy of the Recognition-Retrieval Model (94.71% ± 1.69) is significantly higher than that of the Classification Model (69.66% ± 3.43) and manual sorting (72.50% ± 11.37)

2.3 GAPS IDENTIFIED

- Class Imbalance Handling: Synthetic data generation techniques may lead to unrealistic samples, potentially degrading the model's performance on actual waste data.
- Domain Adaptation and Transfer Learning: Collecting diverse data for domain adaptation is logistically challenging and expensive due to the involvement of multiple waste management facilities or regions.
- Model Interpretability:Balancing model performance and interpretability is challenging as techniques enhancing interpretability may sacrifice prediction accuracy.

3. Dataset

The dataset consists of 6 classes – Electronic waste, Organic waste, Glass, Paper. Metal and plastic were explored for each class.l. Some datasets included images in certain classes where the images were of low quality. In the final dataset, the imagesets which have the highest quality and the highest image count, were included.

4. MATERIALS & METHODS

4.1 EXISTING SYSTEM

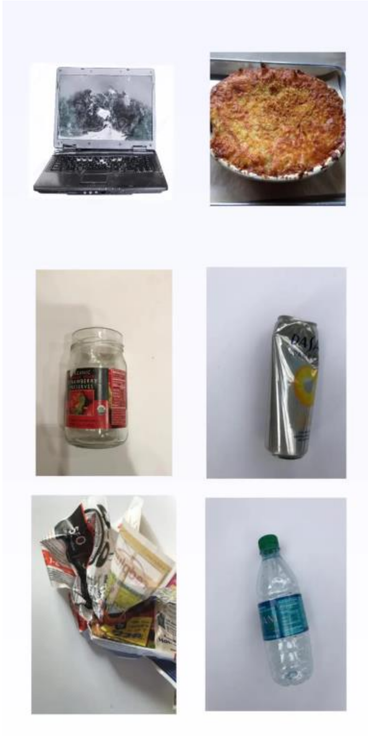
Recycling waste from households and industries is one of the methods that has been proposed to reduce the ever-increasing pressure on landfills. Different types of waste types warrant different management techniques and hence, proper waste segregation according to its types is essential to facilitate proper recycling.the current existing segregation method still relies on a manual hand-picking process. In this paper, a method; based on deep learning and computer vision concepts, to classify wastes using their images into six different waste types (glass, metal, paper, plastic, cardboard, and others) has been proposed. Multiple-layered Convolutional Neural Network (CNN) model, with a trained dataset obtained from online sources. High classification accuracy of 92.5% is achievable using the proposed method. It is envisaged that the proposed waste classification method would pave the way for the automation of waste segregation with reduced human involvement and therefore, helps with the waste recycling efforts

4.2 Proposed system

The proposed system is an innovative solution that aims to revolutionize waste classification and management using advanced technologies. It combines the power of artificial intelligence, machine learning, and computer vision to accurately and efficiently classify various types of waste. The system involves developing robust algorithms that can analyse waste images, extract relevant features, and make precise classifications. By leveraging these technologies, he proposed system offers numerous benefits, including improved accuracy, reduced human error, streamlined waste sorting processes, and enhanced recycling efforts. It has the potential to optimize waste management operations, promote sustainability, and contribute to a cleaner and healthier environment

4.2.1 Sample images

The sample images consist of 6 types of waste that is electronic, food, glass, metal, paper, and plastic. Electronic Waste images are taken from the ”Waste Classification Dataset”[12], Food Waste images are taken from the ”Food-101 Dataset”[13] and the rest are taken from the ”Waste Classification PI”[14].



4.2.2 Data Preprocessing

The goal of data preprocessing is to improve the quality of the data and to make it more suitable for the specific data mining task. One of the key data preprocessing steps involves rescaling the input images. The normalization process ensures consistent ranges and improves convergence during training. Data augmentation techniques are employed to enhance the model’s robustness and generalization capabilities

4.2.3 Data Collection Procedure

The data collection process involved it is necessary to define the waste classes or categories that will be used for classification, such as plastic, paper, glass, metal, or organic waste. Once the waste classes are determined, a diverse dataset of waste images needs to be gathered. This can be achieved by capturing images using a camera or sourcing images from existing databases or online sources.

It is important to ensure that the dataset includes a sufficient number of images for each waste class to enable effective training. Following the gathering of waste images, the next step is to annotate the images with their corresponding waste class labels.

This process involves labeling each image manually or leveraging crowdsourcing platforms or annotation tools. The dataset should be split into training, validation, and testing subsets to facilitate model training and evaluation. To increase the dataset's size and diversity, data augmentation techniques can be applied, such as image rotation, scaling, flipping, or adding noise

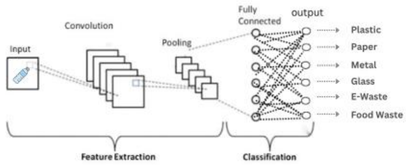
4.2.4 Data Augmentation

Data augmentation techniques were applied to increase the dataset's size and diversity. The Keras ImageDataGenerator class was utilized for augmentation. Augmentation techniques included rotation, horizontal/vertical shifts, zoom, and horizontal flips. Multiple augmented images were generated for each original image, resulting in a larger and more varied dataset.

4.2.5 Data Splitting

The preprocessed and augmented dataset was divided into two subsets: a training set and a testing set. The training set was used to train the model, while the testing set was used to evaluate its performance. This split was performed to ensure that the model's ability to generalize to unseen data could be assessed. During the split, a portion of the dataset was randomly selected for the testing set, while the remaining data formed the training set.

4.6 ARCHITECTURE DIAGRAM



The model defined in the provided code is a CNN architecture commonly used for image classification tasks. Here's an overview of the model's structure:

The model has 6 layers of convolutional layers, 5 layers max pooling layers. Each convolutional layer applies filters to extract features from the input images. The filters have different sizes, specified as (3, 3), and the number of filters increases as the network deepens. The activation function used in the convolutional layers is Rectified Linear Unit(ReLU), which introduces non-linearity and helps capture complex patterns in the data.

Max pooling layers follow each convolutional layer and downsample the feature maps by taking the maximum value within a given window size, which helps reduce the spatial dimensions and extract important features. The last convolutional layer is followed by a flattened layer, which reshapes the 3D feature maps into a 1D vector. The flattened layer connects the convolutional part of the network to the fully connected layers, which are responsible for making the final predictions.

The fully connected layers consist of a dense layer with 512 units and a ReLU activation function, followed by a dropout layer with a dropout rate of 0.5. Dropout is a regularization technique that randomly drops a fraction of the units during training to prevent overfitting. The output layer is a dense layer with 6 units and a softmax activation function. Since the problem is a multi-class classification task with 6 classes, the softmax activation function ensures that the predicted probabilities sum up to 1, representing the class probabilities.

The model is compiled with the Adam optimizer, which is an adaptive learning rate optimization algorithm. The learning rate is set to 0.001. The model uses categorical cross-entropy as the loss function, suitable for multi-class classification tasks. The accuracy metric is used to evaluate the model's performance during training and evaluation

Overall, the defined CNN model consists of multiple convolutional and pooling layers to extract hierarchical features from the input images, followed by fully connected layers for classification. The model aims to learn discriminative features and make accurate predictions for the given image classification problem.

4.7 MODEL TRAINING

The model was trained using the training set, which consisted of pre-processed and augmented data. The training process involved iterating over the dataset for a specified number of epochs. In this case, the model was trained for 82 epochs. A batch size of 32 was used, indicating the number of samples processed before updating the model's internal parameters. During the training process, the model's performance was evaluated to monitor its progress and ensure effective learning

- Fit: The model is being trained using the fit method, which is a common method for training machine learning models in keras, a high level neural networks API written in Python.

- Train data and Test data: These are the data generators for training and validation datasets, respectively. Data generators are used to efficiently load and preprocess data in batches during training to avoid memory issues and improve training speed.
- Steps per epoch: It represents the number of steps (batches) to be processed in each epoch. It is calculated as the total number of training samples divided by the batch size (batch size). Each step processes one batch of training data.
- Epochs:the number of epochs defines how many times the entire training dataset will be processed during training. In this case, the model will be trained for 82 epochs
- Validation data and validation steps: Similar to the training data, these parameters are used for validation during training. The validation data holds the validation dataset (test data), and validation steps specify the number of steps (batches) to be processed in each validation epoch.

During training, the model iteratively goes through the entire training dataset (train data) for 82 epochs. In each epoch, the training data is divided into batches of size batch size, and the model updates its weights using an optimization algorithm.

After each epoch, the model's performance is evaluated on the validation dataset (test data). This provides an estimate of how well the model is generalizing to new, unseen data and helps monitor for overfitting.

The training process continues for 82 epochs, and at the end of the training, the model's final weights will be those that resulted in the lowest validation loss or highest validation accuracy.

5. RESULTS

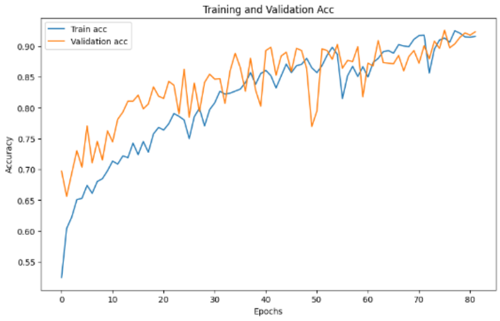
Presenting the results of the experiments. The performance metrics used are,

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

5.1 ACCURACY AND LOSS

After training the model for 82 epochs, the model achieved a training loss of 0.2291 and a training accuracy of 91.59%. The validation loss at the end of the training was 0.2682, with a validation accuracy of 92.32%. These metrics indicate that the model performed well during training, achieving high accuracy and relatively low loss on both the training and test sets.

This indicates that the model generalizes well to unseen data, as it maintains a high level of accuracy and reasonable loss on the test set. The model demonstrates strong performance in terms of accuracy, with a high level of accuracy achieved both during training and evaluation on the test dataset. The loss values indicate that the model effectively minimizes the dissimilarity between predicted and true class probabilities, further supporting its reliability for classification tasks.



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5.2 Precision, Recall, F1 score, Support

The Classification Report is generated to show the following metrics

• Precision: Precision measures the proportion of correctly predicted positive instances(true positives) out of the total instances predicted as positive.

• Recall: Also known as sensitivity or true positive rate, measures the proportion of

correctly predicted positive instances out of the total actual positive instances.

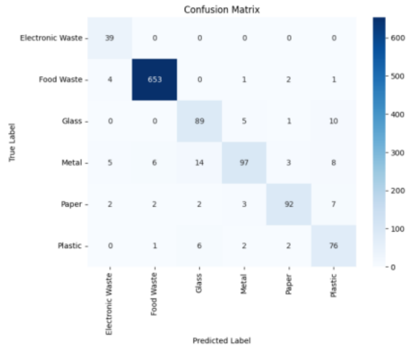
• F1 score: The F1 score is the harmonic mean of precision and recall and provides a

balanced measure of the model's performance.

• Support: Support represents the number of instances in each class. It provides an understanding of the distribution of classes in the dataset.

Overall, the model demonstrates a high level of performance across the precision, recall, and F1 score metrics, indicating its effectiveness in classifying the different classes.

5.3 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

5.4 Evaluation Metrices

To assess the predictive performance of the deep learning models, we employed a range of standard performance metrics. These metrics included accuracy, precision, recall, and F1 score. Accuracy measures the overall correctness of the model's predictions, while precision quantifies the proportion of correctly identified positive cases among all positive predictions. Recall, also known as sensitivity, measures the proportion of correctly identified positive cases among all actual positive cases. The F1 score provides a balanced measure between precision and recall, considering both false positives and false negatives. By evaluating the models using these metrics, we gain a comprehensive understanding of their performance in detecting scoliosis in X-ray images

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

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

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

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

Where *TP* (true positives) is the number of correctly classified images (i.e., for each one of the classes), *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

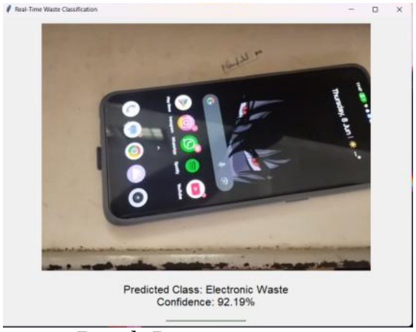
6 .System Requirements

- PyCharm : PyCharm is a popular and powerful integrated development environment (IDE) specifically designed for Python programming, offering a rich set of features to boost developer productivity[
- Python 3 : Python is a dynamic object-oriented programming language that can be used for many kinds of software development. It offers strong support for integration with other languages and tools, comes with extensive standard libraries, and can be learned in a few days. Many Python programmers report substantial productivity gains and feel the language encourages the development of higher quality, more maintainable code
- Google colab : Google Colab, short for Google Colaboratory, is a cloud-based platform that provides a Jupyter Notebook environment for running Python code. It allows users to write, execute, and share code directly in their web browsers without requiring any setup or installation. Google Colab offers free access to powerful hardware resources, including GPUs and TPUs, which can accelerate tasks like training deep learning models. With pre-installed libraries and seamless integration with Google Drive, Colab provides a convenient and collaborative environment for data analysis, machine learning experimentation, and sharing of notebooks
- Tkinter Module : Tkinter is a Python module used for creating graphical user interfaces (GUIs). It provides a set of tools and widgets to design and build interactive desktop applications. Tkinter is easy to use, included with the standard Python installation, and offers various layout managers for organizing GUI components. It supports event-driven programming, allowing developers to define how the application responds to user interactions. With Tkinter, developers can create windows, buttons, menus, and more, making it a popular choice for creating GUI applications in Python
- Jupyter Notebook ; Jupyter Notebook is a web-based interactive computing platform. It allows users to create and share documents called notebooks. Notebooks consist of cells that can contain code or markdown text. It supports multiple programming languages and enables code execution and visualization. It promotes collaborative and reproducible workflows in data analysis and research

7. Implementation

the implementation of waste classification using deep learning techniques to automate and optimize the waste sorting process. By leveraging advanced neural network architectures, specifically CNN, the project aims to accurately categorize and classify different types of waste, such as plastics, paper, glass, metal, food, and electronic wastes. The report discusses the methodology involved in collecting a diverse dataset, preprocessing the data, constructing and training the deep learning model, and evaluating its performance. The trained model achieves a training accuracy of 91.59\% and a validation accuracy of 92.32\%. The report highlights the potential real-world applications of the model in waste sorting facilities and recycling centers, emphasizing the benefits of improved sorting efficiency and resource recovery. The importance of continuous monitoring and periodic retraining of the model for adaptability and effectiveness over time is also emphasized, ultimately contributing to better waste management practices and environmental sustainability.

Home page



Result Page

8 Conclusion & Future Scope

8.1 Conclusion

The overall aim of our topic is to classify the waste material 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. .

8.2 Future scope

The future scope of waste classification using deep learning is promising and holds several potential opportunities. Here are some key aspects to consider: Hyperparameter tuning: Fine-tune the hyperparameters of your model to optimize its performance. This includes parameters such as learning rate, batch size, optimizer, regularization techniques, and dropout rates. Use techniques like grid search or random search to efficiently explore the hyperparameter space.

Class imbalance handling: If the dataset has a class imbalance, where some classes have more examples than others, consider employing techniques to handle this issue.

You can explore oversampling techniques like SMOTE (Synthetic Minority Over-sampling Technique) or undersampling techniques like RandomUnderSampler to balance the class distribution. Model architecture exploration: Experiment with different variations of the CNN model architecture. You can try different numbers of layers, layer sizes, and activation functions, or even explore advanced architectures like residual networks (ResNet) or convolutional neural networks (CNNs) with attention mechanisms.

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