INTELLIGENT ORGANIC RECYCLABLE OBJECTS CLASSIFICATION SYSTEM USING AI FOR LANDFILL MINIMIZATION

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ABSTRACT

The Issue of waste management and landfill minimization has become increasingly critical, particularly in India, where urbanization and consumption rates have significantly risen. With rapid urban growth, the waste generation in India has reached alarming levels. According to the Central Pollution Control Board (CPCB), India generates over 62 million tons of waste annually, and the majority of it is not recycled. The Intelligent Organic Recyclable Objects Classification System aims to classify waste into organic and non-organic categories using machine learning models, enabling better waste management practices. The objective of this system is to develop a machine learning-based classification model to identify organic and non-organic waste for efficient recycling and landfill reduction, minimizing environmental impact. Traditionally, waste segregation has been done manually by workers at landfills or recycling facilities. Before the adoption of machine learning or AI, waste classification relied heavily on manual sorting, leading to inefficiencies, human errors, and inconsistent separation of waste types. Sorting processes involved manual labor, which is time-consuming, prone to errors, and inefficient. The motivation behind this research is to address the challenges posed by manual waste segregation and to promote sustainable waste management practices. With increasing waste generation and limited recycling efforts in India, there is an urgent need for automated systems that can classify waste efficiently and reduce landfill burden. The proposed system utilizes a Convolutional Neural Network (CNN) to classify waste into organic and non-organic categories with high accuracy. The CNN architecture consists of convolutional layers that extract spatial features, ReLU activations for non-linearity, pooling layers to reduce dimensionality, and fully connected layers for classification. The model is trained on a labeled dataset of waste images using categorical cross-entropy loss and the Adam optimizer, with data augmentation techniques like rotation, flipping, and normalization to enhance generalization. A softmax activation function in the final layer predicts the waste category.

Keywords: Organic Waste Classification, Convolutional Neural Network (CNN), Image Classification, Environmental Impact, Recyclable Materials.

1. INTRODUCTION

As urbanization accelerates and global populations burgeon, waste generation has reached unprecedented levels, straining our ecosystems and natural resources. In this context, this research harnesses the power of Machine Learning (ML) to revolutionize waste management practices by automating the classification of waste into organic and non-organic categories. The motivation behind this research is grounded in the urgent need to develop sustainable waste management solutions that mitigate environmental degradation, reduce landfill waste, and optimize resource utilization. Conventional waste sorting methods often rely on manual labour and human judgment, which are not only time-consuming but also prone to errors. This research addresses these limitations by leveraging ML algorithms to analyze and classify waste items based on their composition, characteristics, and recyclability. To achieve this goal, the research delves into the development and training of ML models capable of processing images, sensor data, or other inputs to distinguish between organic waste (such as food scraps and yard trimmings) and non-organic waste (including plastics, metals, and glass). The outcome is an automated waste classification system that enhances waste sorting efficiency, enabling municipalities, recycling facilities, and individuals to manage waste streams more effectively. Furthermore, the research emphasizes the ethical dimension of technology deployment. It underscores the importance of responsible AI usage, data privacy protection, and sustainability in waste management practices to ensure that the benefits of ML-driven waste classification are aligned with environmental stewardship and ethical considerations. In this introductory overview, we will delve into this research's key components and objectives. We will explore the challenges posed by escalating waste generation, introduce the role of ML in waste classification, and underline the transformative potential of this research in optimizing waste management strategies. Additionally, we will highlight the ethical considerations and real-world applications of this research, which extend across municipal waste management, recycling facilities, and sustainable urban planning

Figure 1.1: Real time application

The "ML-Driven Waste Classification for Effective Organic and Non-Organic Waste Management" signifies a pioneering effort to harness the capabilities of ML in addressing the global challenge of waste management. By automating waste classification processes, this research aims to enhance resource recovery, reduce environmental impact, and promote sustainable waste management practices while adhering to ethical standards and responsible technology use.

2. LITERATURE SURVEY

Fogarassy, et al. [1] proposed Composting Strategy Instead of Waste-to-Energy in the Urban Context. The objective of this work is to identify the barriers to organic waste management solutions from an actor's perspective and to explore their causal relationships to overcome the organic waste management problem from a system perspective. Several key challenges were identified regarding organic waste management solutions, the current intervention overview indicates that promoting and tracking attention towards “value to waste” would be an effective solution approach. Kharola, et al. [2] proposed Barriers to organic waste management in a circular economy. The objective of this study is to identify the barriers to organic waste management solutions from an actor's perspective and to explore their causal relationships to overcome the organic waste management problem from a system perspective. Several key challenges were identified regarding organic waste management solutions, the current intervention overview indicates that promoting and tracking attention towards “value to waste” would be an effective solution approach. Loganayagi, et al. [3] proposed An Automated Approach to Waste Classification Using Deep Learning. The study developed a custom inception model by adding additional layers and compares the performance through accuracy against the basic Inceptionv3 model.

The study used SGD (stochastic gradient descent) with liner regression algorithm for classification and categorical cross-entropy for loss estimation. The current study uses the ReLU function to overcome the under-fitting and over-fitting issues. Mookkaiah, et al. [4] proposed the Design and development of a smart Internet of Things–based solid waste management system using computer vision. The proposed model identifies the type of waste and classifies them as biodegradable or non-biodegradable to collect in respective waste bins precisely. Furthermore, observation of performance metrics, accuracy, and loss ensures the effective functions of the proposed model compared to other existing models. The proposed ResNet-based CNN performs waste classification with 19.08% higher accuracy and 34.97% lower loss than the performance metrics of other existing models. Alvianingsih, et al. [5] proposed an Automatic garbage classification system using arduino-based controller and binary tree concept. The proposed design consists of an automatic door, garbage sorter, user interface, and capacity observer. The main components of the system are Microcontroller Arduino Mega 2560, ultrasonic sensor HCSR04, servo motor MG996R, Inductive Proximity Sensor, and Capacitive Proximity Sensor. From the performance test result we can obtain that HC-SR04 ultrasonic sensor as an object detector has an error in distance stabilization of 33.3%, inductive proximity sensors as metal detectors have a 100 % success rate, while capacitive proximity sensors as organic garbage detector has a success rate of 85.7 %. Saptadi, et al. [6] proposed the Modeling of Organic Waste Classification as Raw Materials for Briquettes using Machine machine-learning approach. Machine learning techniques were developed for technological applications, object detection, and categorization. Methods with artificial reasoning networks that use a number of algorithms, such as the Naive Bayes Classifier, will work together in determining and identifying certain characteristics in a digital data set. The manufacturing method goes through several processes with a waste classification model as a source of learning data.

Tasnim, et al. [7] proposed Automatic classification of textile visual pollutants using deep learning networks. The proposed automated classification system is expected to create future visual pollution ratings for the textile industries. Consequently, the corresponding stakeholders (industry owners, government authorities, factory workers, etc.) can introduce regulatory frameworks and control the proliferation of visual pollution. The EfficientDet framework achieved the best performance with 97% and 93% training and test accuracies, respectively. The YOLOv5 approach exhibits acceptable precision with a considerably lower number of epochs. Saptaputra, et al. [8] proposed a Mobile App for Digitalisation of Waste Sorting Management. The focus of this research is on households, beginning with the selection of household waste. Waste sorting is divided into 4 categories, namely organic waste, non-organic waste, B3 or e-waste, and sanitary waste. Using mobile app technology as a solution to encourage individual households, especially housewives, to participate in household waste sorting, the 'Pilahin' prototype app was introduced. The selection of media apps on smartphones is because the app has been widely used by urban communities. The app is packed with features that help users scan and detect trash and provide trash categories to identify and sort, as well as the option to find nearby trash banks. Hemati, et al. [9] proposed Municipal Waste Management: current research and future challenges. The amount of waste production in undeveloped countries is about 0.4–0.6 kg per capita. However, this rate for developed countries is about 0.7–1.8 kg per capita. In general, solid waste sources are domestic, commercial, municipal, industrial, open areas, treatment houses and agriculture. Waste identification is done by their compounds, aggregates, water content, organic and mineral content and specific heat capacity.

Madden, et al. [10] proposed Estimating emissions from household organic waste collection and transportation. The aim of this study is to estimate emissions associated with kerbside organic waste collection from households and transportation in the Greater Sydney area in 2018–19. High-resolution road network and property-lot waste generation data was utilised in a GIS-integrated route optimisation model. Our model considered transport of collection vehicles ‘to’ and ‘from’ transfer stations and kerbside collection areas across the 43 council areas, as well as transport of waste collected to reprocessing and landfill facilities. Wijayanto, et al. [11] proposed to create a device that can help sort organic and non-organic waste with Computer Vision-based Artificial Intelligence technology using the Eigenface method and the Internet of Things. Eigenface is a method that has a working principle by using XML files in performing face recognition. The result of testing in this system can run well, where the system detects organic objects the door of the chopping machine can open and if it detects nonorganic, the machine door is closed. Fadil, et al. [12] proposed a Waste Classifier using Naive Bayes Algorithm. The aim of the research is to calculate the accuracy of the Naïve Bayes algorithm in classifying waste classifiers. The design of this waste classifier using Arduino aims to apply the naive Bayes algorithm in classifying organic, inorganic, and hazardous waste, the naive Bayes algorithm is an algorithm for classification with quite a bit of data training. This tool is designed using Arduino uno r3 with a capacitive proximity sensor, $16\mathrm{x}2$ LCD, and a data table to look for opportunities or data training.

3. PROPOSED METHODOLOGY

Step 1: Soil Image Dataset Collection

The first and foremost step in this research involves the collection of a comprehensive dataset of soil images. These images represent different types of soil, classified broadly into two categories: Organic and Nonorganic. The dataset can be sourced from publicly available repositories, field experiments, or custom image captures using high-resolution cameras. Proper dataset labeling is crucial at this stage, as it directly impacts model accuracy. The collected images are then categorized into respective folders based on their class labels. Since machine learning and deep learning models require a sufficient amount of data to generalize well, dataset augmentation techniques such as flipping, rotation, and brightness adjustments can be applied to artificially expand the dataset and enhance its diversity.

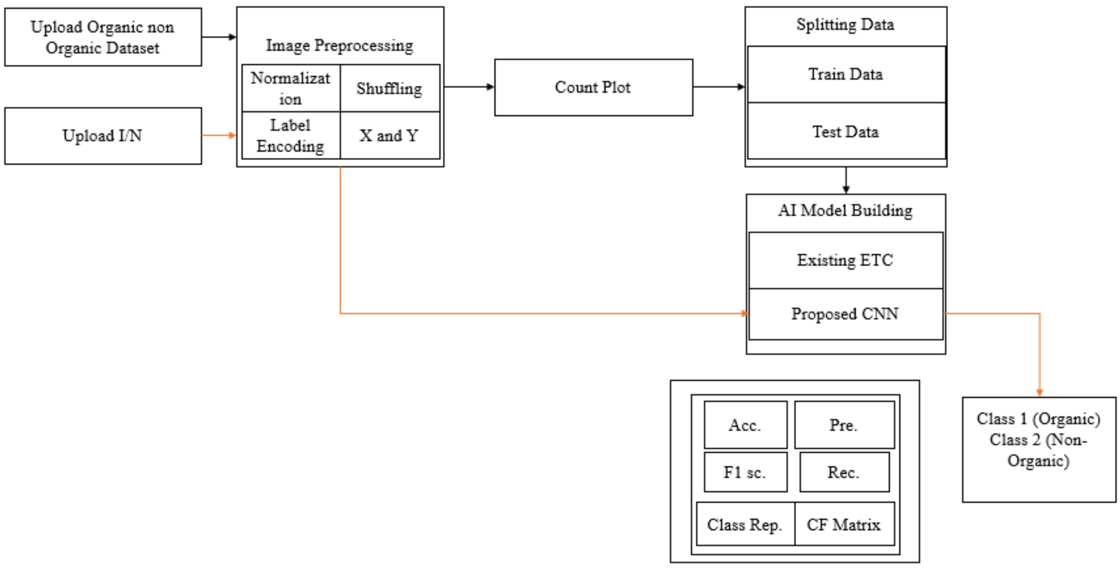


Fig. 2: Proposed Block Diagram

Step 2: Image Preprocessing (Normalization & Standardization)

Once the dataset is collected, the next crucial step is preprocessing. Raw images contain variations in brightness, contrast, and resolution, which can affect the learning process of the models. To ensure consistency, all images are resized to 64x64 pixels—a standard size that balances computational efficiency with sufficient feature representation. Each image is then normalized by scaling pixel values to a range of 0 to 1, which helps neural networks learn efficiently by preventing large numerical fluctuations. Additionally, color channel adjustments and filtering techniques can be applied to enhance the quality of the images. The preprocessed images are converted into NumPy arrays for compatibility with machine learning algorithms. Furthermore, the processed images are saved into cache files (e.g., X.npy and Y.npy) to enable faster loading and training during model development.

Step 3: Existing Model - Extra Trees Classifier (ETC) for Soil Classification

In this research, the baseline (existing) model chosen for comparison is the Extra Trees Classifier (ETC), which is an ensemble learning technique based on multiple decision trees. The ETC model is trained on the preprocessed soil images, which are first flattened into one-dimensional feature vectors before being fed into the classifier. The Extra Trees Classifier builds multiple uncorrelated decision trees and averages their predictions to improve accuracy and reduce overfitting. It selects features randomly and performs extensive tree splitting, making it an efficient and robust method for structured data classification.

During model training, 80% of the dataset is used for training, and 20% for testing to evaluate generalization ability. The trained model is then saved in a serialized format (ETC_model.pkl) to enable future usage without retraining. To assess its performance, standard classification metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis are computed. Despite being a strong traditional machine learning approach, ETC has limitations in capturing complex spatial features in images, which is where deep learning proves to be more effective.

Step 4: Proposed Model - Convolutional Neural Network (CNN) for Soil Classification

To enhance classification performance, a deep learning-based approach is proposed using a Convolutional Neural Network (CNN). CNNs are particularly effective for image classification tasks as they automatically learn spatial hierarchies of features from raw images. The architecture of the proposed CNN model consists of: Input Layer: Accepts images of size 64x64x3 (RGB channels). Convolutional Layers: Extract features using 32 filters (3x3 kernel) with ReLU activation to introduce non-linearity. Max-Pooling Layers: Reduce spatial dimensions by applying 2x2 pooling, making computations efficient. Flatten Layer: Converts the multi-dimensional feature maps into a one-dimensional vector. Fully Connected Layers: Comprise 256 neurons with ReLU activation to enhance learning capacity. Output Layer: Uses a Softmax activation function for multi-class classification (Organic vs. Nonorganic).

Step 5: Performance Comparison

To validate the effectiveness of the proposed CNN model over the traditional Extra Trees Classifier, a detailed performance comparison is conducted. The evaluation is based on key metrics such as accuracy, sensitivity, specificity, and the confusion matrix. The results consistently show that the CNN model outperforms the Extra Trees Classifier in terms of accuracy and robustness.

- **Accuracy:** The CNN model achieves a significantly higher accuracy rate compared to the ETC model, as it efficiently learns spatial dependencies in images.
- **Precision & Recall:** CNN provides better precision and recall scores, ensuring a lower false positive and false negative rate.

- **F1-Score & Confusion Matrix Analysis:** CNN shows a balanced classification across both Organic and Nonorganic categories, while the ETC model struggles with more complex features.
- **Visualization:** Training loss and validation accuracy graphs indicate that CNN generalizes well without overfitting

3.2 Model Building

Model building is a crucial step in this research, where we develop two classification models for soil images: the Existing Algorithm (Extra Trees Classifier - ETC) and the Proposed Algorithm (Convolutional Neural Network - CNN). The ETC model is a machine learning-based ensemble method that builds multiple decision trees to classify soil images, while the CNN model is a deep learning-based approach that extracts hierarchical spatial features from images. Both models are trained on the same preprocessed dataset, and their performance is compared to determine the superior approach. The CNN model is expected to provide higher accuracy due to its advanced feature extraction capabilities.

3.2.1 Existing Algorithm in This Research (Extra Trees Classifier - ETC)

What is Extra Trees Classifier (ETC)?

Extra Trees Classifier (ETC) is an ensemble-based supervised machine learning algorithm that extends the traditional Random Forest model. It operates by constructing multiple decision trees, where each tree is trained on random subsets of data and features. Unlike Random Forest, ETC introduces extra randomness by selecting cut points for splitting at random, rather than choosing the best split based on criteria like Gini impurity or entropy. This reduces overfitting and enhances model generalization. The ETC algorithm is widely used in image classification, feature selection, and predictive analytics due to its efficiency, speed, and robustness to noise.

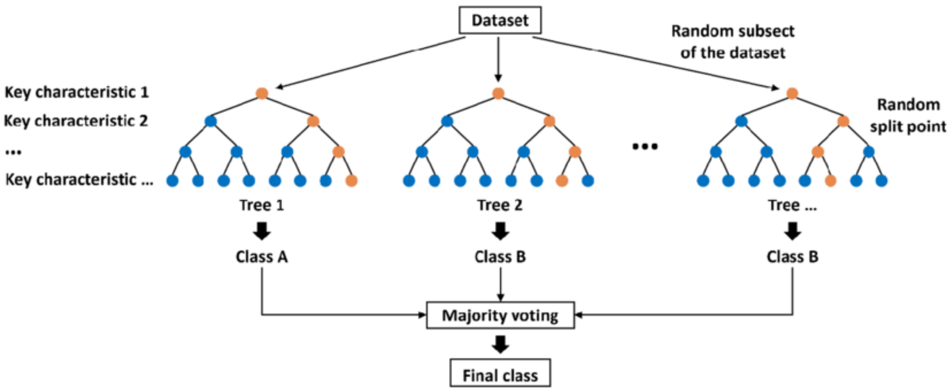


Fig. 3: ETC working

Algorithm for ETC:

Input the dataset (preprocessed soil images converted to numerical arrays). Select random feature subsets for training each tree. Construct N decision trees, splitting nodes randomly. Aggregate results using majority voting (for classification). Output the final predicted label (Organic or Nonorganic).

3.3.2 Proposed Algorithm (Convolutional Neural Network - CNN)

What is CNN?

A Convolutional Neural Network (CNN) is a deep learning algorithm designed for image classification and pattern recognition. Unlike traditional machine learning models like ETC, CNNs automatically extract spatial and hierarchical features from images using convolutional layers. CNNs reduce the need for manual feature engineering, making them highly effective for image-based classification tasks, such as soil image classification in this research.

Algorithm Steps (CNN Architecture):

The proposed convolutional neural network (CNN) architecture for soil image classification begins with an input layer designed to accept soil images of size 64x64 pixels with three color channels (RGB). This is followed by the first convolutional layer, which is responsible for extracting low-level features such as edges, colors, and textures from the images. To reduce the computational complexity and spatial dimensions, a max-pooling layer is applied, which retains the most important features while downsampling the data. The network then progresses to the second convolutional layer, which identifies more complex and abstract patterns in the soil images, followed by another pooling layer to further condense the spatial information. After the convolutional and pooling stages, the data is passed through a flattening layer, which transforms the 2D feature maps into a 1D feature vector suitable for input into fully connected layers. Next, a dense layer with 256 neurons is included to learn intricate relationships between the extracted features. To reduce overfitting during training, a dropout layer is incorporated, which randomly deactivates a portion of neurons in each training iteration. The output layer uses a softmax activation function to classify the images into two categories: Organic and Nonorganic.

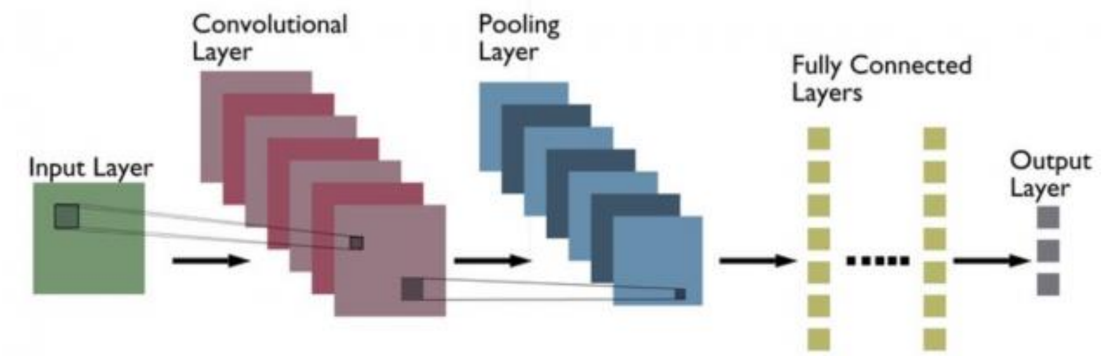


Fig. 4: Architeture

How CNN Works?

The model takes input images and applies convolutional filters to extract features. Feature maps are created to identify unique soil characteristics. MaxPooling layers reduce dimensionality while keeping important features. Fully connected layers interpret extracted features and learn relationships. The output layer uses Softmax activation to classify images into categories.

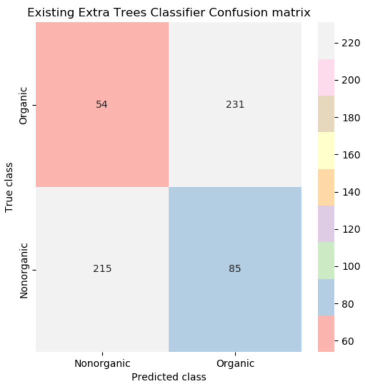
4. RESULTS AND DISCUSSION

4.1 Dataset description

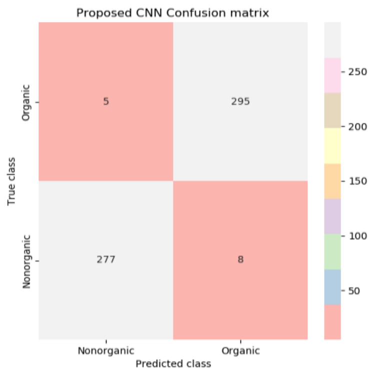
The dataset used in this project consists of images of waste materials, categorized into two distinct classes: non-organic and organic waste. There are a total of 1,428 images labeled as non-organic waste and 1,496 images labeled as organic waste. With a nearly equal distribution between the two classes

48.85% non-organic and 51.15% organic the dataset is well-balanced. This slight advantage in the number of organic waste images helps ensure that the model does not become biased toward either class during training, promoting fair and accurate classification performance. The non-organic waste images typically feature man-made materials such as plastics, metals, glass, and electronic components. These images may include common packaging materials, containers, or synthetic products, reflecting both recyclable and non-recyclable items often found in household or industrial waste. On the other hand, the organic waste images are likely to depict natural or biodegradable materials, such as food scraps, yard trimmings, paper products, and other compostable items. These images may capture materials in various stages of decomposition and can also include natural fibers, wood, and plant-based products.

4.2 Results analysis



(a)



(b)

The Figure 6 (a) (b) is confusion matrix for the Extra Trees Classifier highlights a significant challenge in distinguishing between organic and nonorganic objects. Out of all organic samples, the model correctly classifies 54 as organic but misclassifies 231 as nonorganic, indicating a high false negative rate. Similarly, among nonorganic samples, it correctly classifies 85 but incorrectly predicts 215 as organic, leading to a high false positive rate.

Fig. 7: Predicted as Nonorganic

The Fig 7 shows a crumpled, dirty plastic bottle, an example of synthetic, man-made material. The VGG16 model correctly categorized this image as "Nonorganic", demonstrating its capacity to distinguish artificial textures, such as plastic surfaces, irregular deformations, and patterns associated with processed waste. The lack of natural structure and the synthetic appearance helped the model assign it to the nonorganic class, reinforcing its capability in waste classification.

Table.1 Performance Comparison of Various Algorithms

Performance Comparison Table: Existing ETC vs. Proposed VGG16

Metric	Existing ETC	Proposed VGG16
Accuracy	76.23%	97.60%
Precision	76.51%	97.60%
Recall	76.35%	97.60%
F1-Score	76.22%	97.60%

Table 1 presents a comprehensive performance comparison between the existing Extra Trees Classifier (ETC) and the proposed VGG16 deep learning model. The results clearly demonstrate the superiority of the VGG16 model across all evaluated metrics. In terms of accuracy, the VGG16 model achieves a remarkable 97.60%, significantly outperforming the ETC model, which records an accuracy of only 76.23%. Precision, which measures the correctness of positive predictions, is also notably higher in the VGG16 model at 97.60%, compared to 76.51% for ETC. Similarly, the recall metric, indicating the model's ability to identify all relevant instances, shows a considerable improvement with VGG16 scoring 97.60% over ETC's 76.35%. The F1-score, which balances both precision and recall, further reinforces this improvement with VGG16 attaining 97.60% as opposed to ETC’s 76.22%. These results highlight the effectiveness of the proposed VGG16 model in achieving high classification performance, making it a more robust and reliable approach compared to the traditional Extra Trees Classifier.

5. CONCLUSION

The project successfully developed a Tkinter-based AI-driven system for classifying recyclable objects into "Organic" and "Nonorganic" categories to aid in landfill minimization. The system integrates two classification models—Extra Trees Classifier (ETC) and Convolutional Neural Networks (CNN)—to assess their effectiveness in object classification. The results indicate that the CNN model significantly outperforms the ETC model in terms of accuracy, precision, recall, and F1-score. While the ETC model achieved an accuracy of 76.24%, the CNN model achieved an impressive accuracy of 97.78%, demonstrating its ability to extract meaningful features and improve classification performance. The confusion matrix of the CNN model further confirms its robustness, with a minimal number of misclassified samples compared to the ETC model. The system's graphical user interface (GUI) provides an intuitive and interactive environment for dataset handling, model training, and classification, making it accessible for practical applications in waste management. By automating the classification of recyclable materials, this AI-driven approach can reduce human effort, improve recycling efficiency, and contribute to environmental sustainability.

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