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Intelligent Organic Recyclable Objects Classification System using AI for Landfill Minimization

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ABSTRACT

Rapid urbanization and rising consumption in India have pushed annual waste generation beyond 62 million tons, yet the majority remains uncycled, exacerbating environmental degradation and landfill pressures. Traditionally, waste segregation has relied on labour-intensive manual sorting at landfills and recycling facilities—an approach fraught with inefficiencies, human error, and inconsistent separation of organic and non-organic materials. To overcome these challenges and promote sustainable waste management, this research proposes an intelligent organic recyclable objects classification system, which harnesses convolutional neural networks (CNNs) to automate waste categorization with high accuracy. Our system extracts spatial features from waste imagery via convolutional layers, applies ReLU activations for non-linearity, reduces dimensionality through pooling layers, and employs fully connected layers topped with a softmax output for final class prediction. Trained on a labeled dataset of organic and non-organic waste images, the model optimizes categorical cross-entropy loss using the Adam optimizer and incorporates data augmentation—rotation, flipping, and normalization—to bolster generalization. By reliably distinguishing between biodegradable and synthetic refuse in real time, this machine learning–driven approach aims to streamline recycling workflows, minimize landfill burden, and mitigate the environmental impact of India's burgeoning waste streams.

Keywords: Waste management, Landfill minimization, Image classification, Deep learning, Convolutional neural networks.

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 [1]. 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 [2]. 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

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effectively [3]. 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 [4]. 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 [5].

Figure 1: Real time application scenario.

This research signifies a pioneering effort to harness the capabilities of ML in addressing the global challenge of waste management [6]. 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. [11] 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. [12] 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. [13] 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

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issues. Mookkaiah, et al. [14] 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. [15] 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. [16] 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. [17] 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. [18] 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. [19] 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. [20] 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

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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. [21] 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. [22] 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. Nasirly, et al. [23] proposed Identification the Structure of the Waste Supply Chain for Circular Economy. This study uses a descriptive method with a qualitative approach. The study found that the town of Pangkalan Kerinci Environmental service have serve 72% of the town area, using 19 vehicles (dumping truck), 19 routes for trash collection, 4 collapsible vehicles (bin container truck), and motorcycles for non-accessible locations. Problems found in waste management in Pangkalan Kerinci are; the lack of waste banks and garbage bins, lack of personnel in transporting and sorting, lack of excavators in the landfill facility, and the short supply of dump trucks and trash collecting vehicles.

Aarthi, et al. [24] proposed A vision-based approach to localize waste objects and geometric features exaction for robotic manipulation. A method is proposed for real-time automatic waste material detection and segregation for easier recycling. The proposed approach uses the State-of-the-art deep learning architecture Mask RCNN to locate and classify waste objects from the natural environment. Further, the geometric features like centroid, orientation, and clamping points of the objects are extracted to aid the robotic arm in grasping the waste object. Achmad, et al. [25] proposed Waste management an Islamic perspective. The primary goal of the study is to pinpoint the elements that determine the community of Batu Bantar Gebang's involvement in the creation of a waste bank. Methods of qualitative research were applied in this study. Interviews, field observations, and a review of relevant books and periodicals were all used to gather data for the study. The Ummu Amanah Foundation in Sumur Batu District, Al-Falah School, in Bantar Gebang, Bekasi, West Java, served as the study's location.

3. PROPOSED SYSTEM

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.

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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.

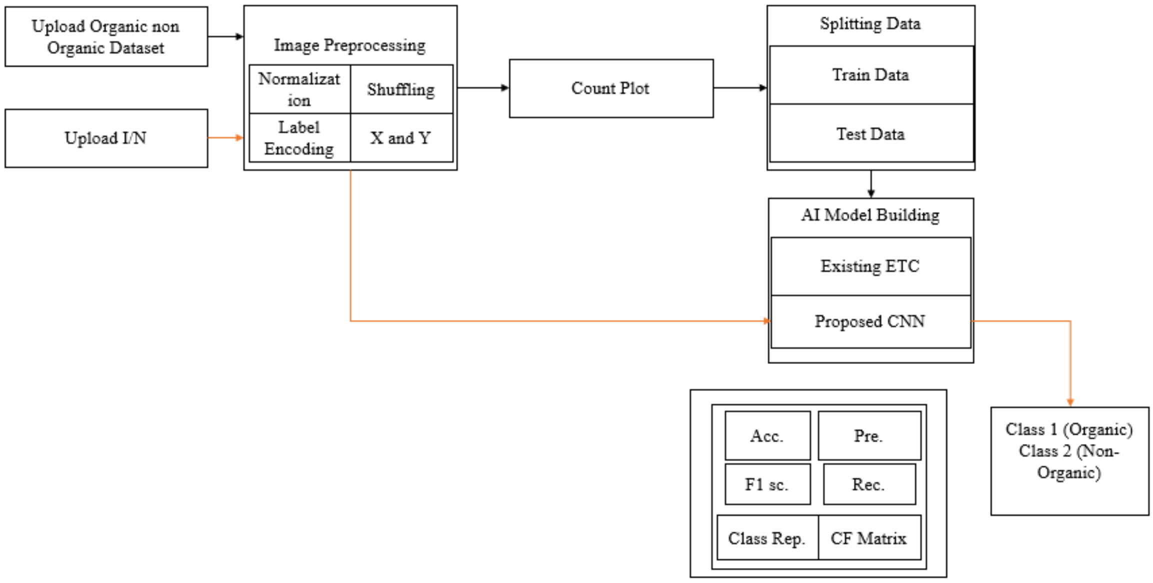

Figure 2: Proposed system block diagram of organic and non-organic classification.

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

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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).

The model is trained using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss function. Training is conducted for 20 epochs with a batch size of 16, and the learned weights are saved in DLmodel_weights.h5, while the model architecture is stored in DLmodel.json. To ensure robustness, data augmentation techniques such as horizontal flipping and brightness adjustments are applied. The CNN model is then evaluated using the same metrics as the ETC model, including accuracy, precision, recall, F1-score, and confusion matrices.

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

3.1 Data splitting & image pre-processing

In this research, data splitting and image pre processing play a crucial role in ensuring effective model training and evaluation. The collected dataset, consisting of soil images classified into Organic and Nonorganic categories, is first divided into two main subsets: Training Set (80%) and Testing Set (20%). This standard split ensures that the model learns from a significant portion of the dataset while also being evaluated on unseen data, allowing for an unbiased assessment of its generalization ability. The

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training set is used to optimize the model parameters, while the testing set serves as an independent benchmark to measure classification performance. After data splitting, the next step involves image preprocessing, which is essential for enhancing image quality and standardizing input data. The raw soil images vary in resolution, brightness, contrast, and background noise, which can introduce inconsistencies during training. To overcome this, all images are resized to a fixed dimension of 64x64 pixels, ensuring uniformity across the dataset. Additionally, normalization is applied by scaling pixel values between 0 and 1. Once preprocessing is complete, the processed images are converted into NumPy arrays and stored for efficient loading during model training. These steps collectively ensure that the dataset is clean, well-structured, and optimized for accurate classification using both machine learning (Extra Trees Classifier) and deep learning (CNN) models.

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.

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. The proposed CNN architecture is as follows:

Step 1. Input Layer: Accepts 64x64x3 soil images.

Step 2. Convolutional Layer 1: Extracts low-level features like edges, colors, and textures.

Step 3. Pooling Layer 1 (MaxPooling): Reduces spatial dimensions and computation.

Step 4. Convolutional Layer 2: Captures higher-level patterns in the soil images.

Step 5. Pooling Layer 2: Further reduces dimensions while retaining key features.

Step 6. Flattening Layer: Converts 2D feature maps into a 1D feature vector.

Step 7. Fully Connected Layer: Dense layer with 256 neurons learns complex relationships.

Step 8. Dropout Layer: Prevents overfitting by randomly deactivating neurons.

Step 9. Output Layer (Softmax Activation): Classifies images into Organic and Nonorganic categories.

Step 10. Optimization & Training: Uses Adam optimizer and categorical cross-entropy loss for backpropagation.

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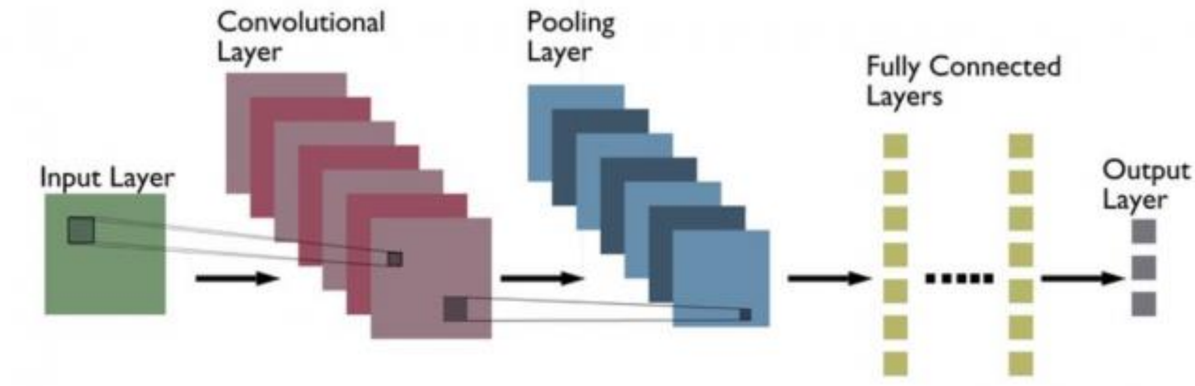

Figure 3: CNN layered architecture,

How CNN Works?

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

4. RESULTS AND DISCUSSION

This waste-classification dataset comprises 2,924 labeled images divided almost equally between two categories—Non-organic waste (1,428 images, 48.85 %) and Organic waste (1,496 images, 51.15 %)—providing near-balanced class representation to minimize bias during model training.

Category	**Number of Images**	**Percentage**
Non-organic	1,428	48.85 %
Organic	1,496	51.15 %
Total	**2,924**	100.00 %

Non-organic Waste Images (1,428): These images likely feature discarded manufactured materials—plastics, metals, glass, and electronics. You may see packaging (bottles, wrappers), containers, or other synthetic products, both recyclable and non-recyclable.

Organic Waste Images (1,496): These photographs typically show biodegradable matter such as food scraps, yard trimmings, paper products, and natural fibers. They may capture organic materials at various decomposition stages, including wood fragments and plant-based refuse.

Figure 4, and Figure 5 demonstrates the sample non-organic and organic images presented in the training dataset, where the non-organic includes waste materials like plastic, dump yard, glass, etc. and the organic includes, fruits, and vegetables etc.

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Figure 4: Sample non-organic images from training dataset.

Figure 5: Sample organic images from training dataset.

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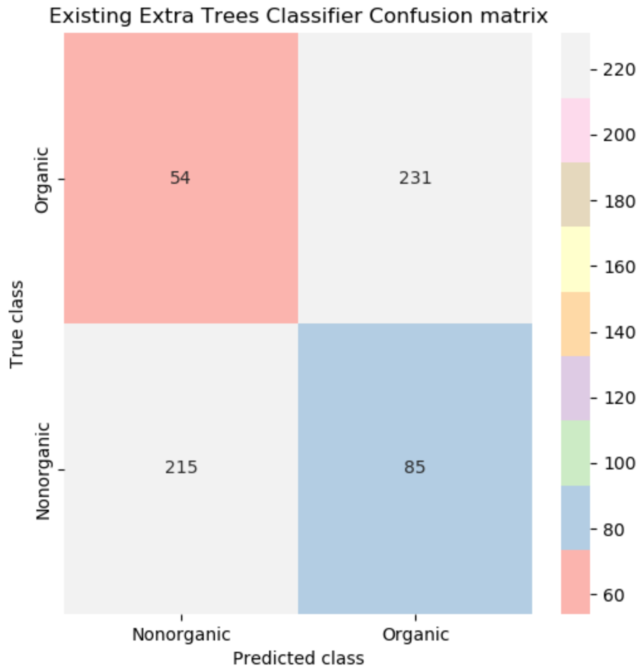

Figure 6: CF Matrix of ETC

The Figure 6 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.

Figure 7 shows that the confusion matrix for the proposed CNN model demonstrates a significant enhancement in classification performance. Out of all the Organic samples, 295 were correctly classified, but 5 were misclassified as Nonorganic. Similarly, for the Nonorganic category, 277 were accurately identified, while only 8 were incorrectly labeled as Organic. This suggests that the CNN model exhibits high sensitivity and specificity, with only a minimal number of misclassifications. Compared to the Extra Trees Classifier, which showed a much higher number of false positives and false negatives, the CNN model has drastically reduced misclassification errors, reinforcing its suitability for accurate organic vs. nonorganic classification.

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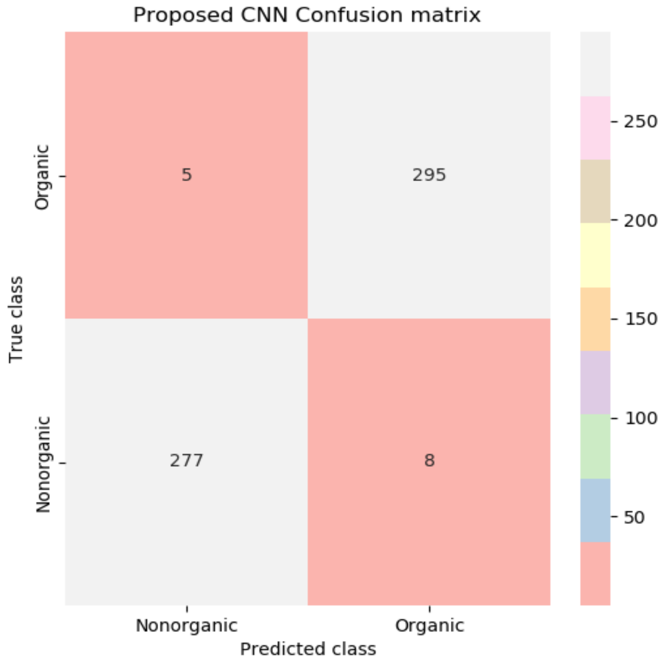
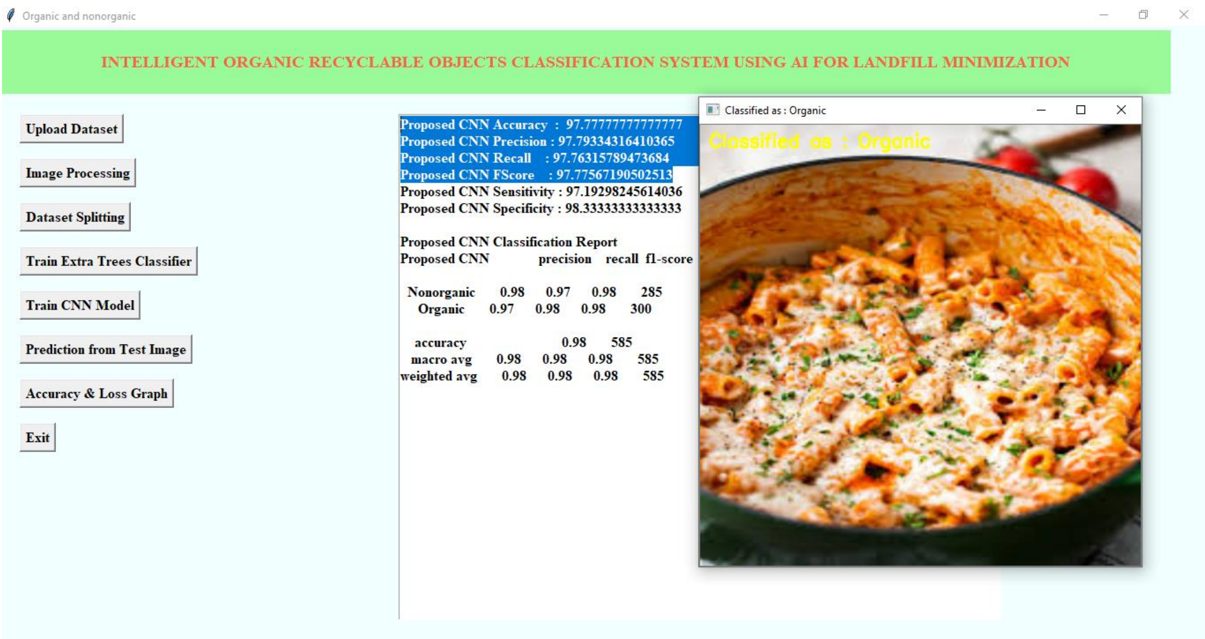


Figure 7: Confusion matrix obtained using proposed CNN model.

The training and validation accuracy/loss curves in Fig. 9 illustrate the performance of the proposed CNN model over 20 epochs. The accuracy plot (top graph) shows that training accuracy continuously improves, reaching nearly 98%.



(a)

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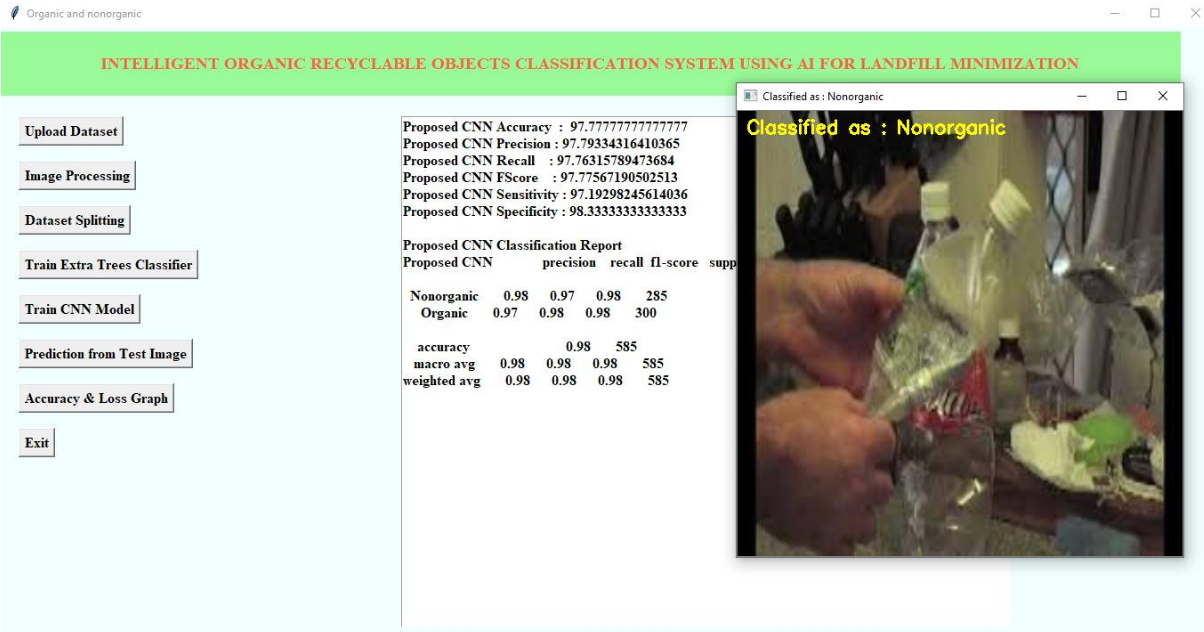

(b)

Figure 8: Sample predictions. (a) predicted as organic. (b) predicted as non-organic.

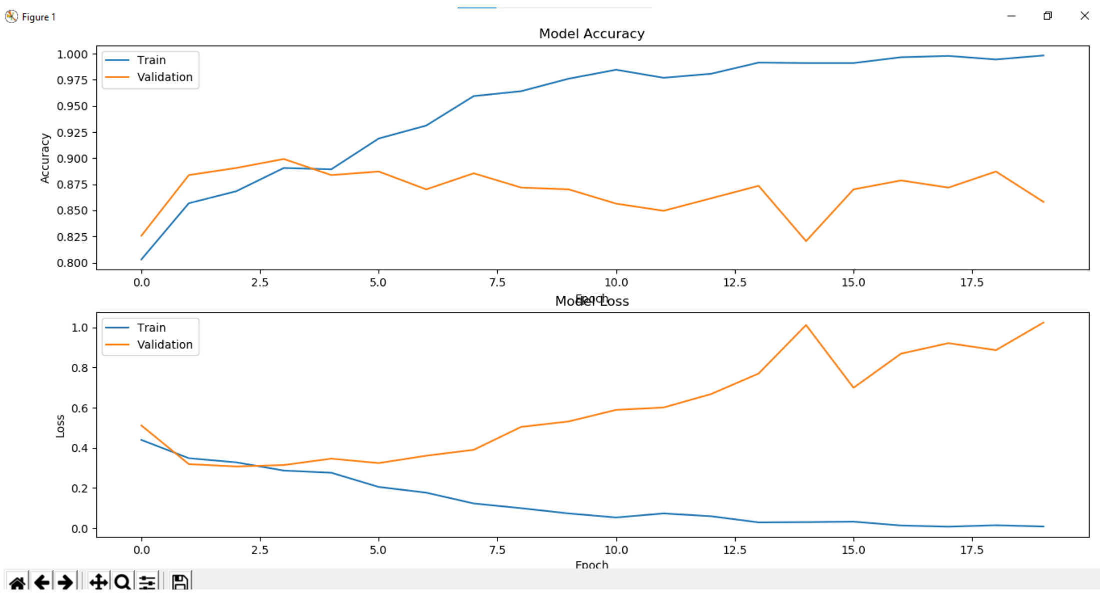

Figure 9: Accuracy loss graph.

5. CONCLUSION

This study 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

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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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