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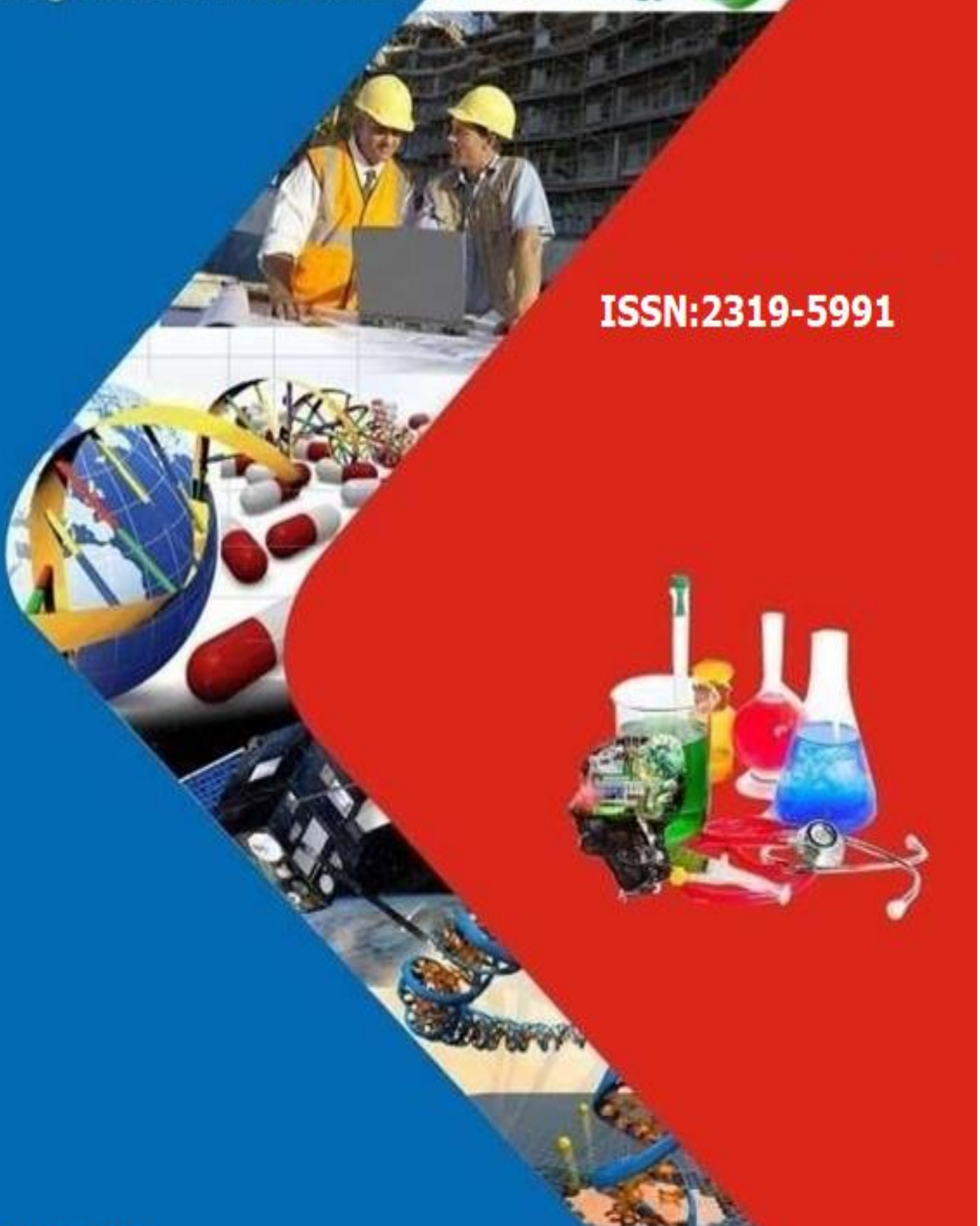

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INTELLIGENTORGANICRECYCLABLEOBJECTSCLASSIFICATION SYSTEM USING AI FOR LANDFILL MINIMIZATION

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ABSTRACT

Because of the dramatic increase in both urbanization and consumption rates, the problem of waste management and the reduction of landfill use has assumed paramount importance, especially in India. The degree of garbage produced in India has reached worrying heights due to the country's fast urbanization. The bulk of India's 62 million tones of trash is not recycled, according to the Central Pollution Control Board (CPCB). To improve garbage management, the Intelligent Organic Recyclable Objects Classification System use machine learning models to sort trash into organic and non-organic groups. In order to reduce landfill use and maximize recycling efficiency while keeping environmental impacts to a minimum, this system aims to create a classification model that uses machine learning to distinguish between organic and non-organic trash. Employees at landfills and recycling centres have historically separated trash by hand. Humans used to sort garbage by hand, which was slow, prone to mistakes, and didn't always separate different kinds of trash. This was before machine learning and AI were widely used. Traditional sorting methods relied on labor-intensive, error-prone, and wasteful physical labor. Addressing the issues of manual trash segregation and promoting sustainable waste management methods are the motivations driving this study. Automated systems that can sort garbage effectively and lessen the load on landfills are desperately needed in India, where garbage production is on the rise but recycling efforts are low. The suggested method achieves remarkable accuracy in trash classification by using a Convolutional Neural Network (CNN). In a convolutional neural network (CNN), spatial feature extraction occurs in convolutional layers; non-linearity is addressed by ReLU activations; dimensionality reduction occurs in pooling layers; and classification is performed by fully connected layers. In order to train the model, we use a tagged dataset of trash photos and data augmentation methods including normalization, rotation, and flipping to improve generalization, along with categorical cross-entropy loss and the Adam optimizer.

Keywords: Normalization, Object classification, Convolutional Neural Network.

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1. INTRODUCTION

1.1 Overview

Waste production has reached historic levels, putting a pressure on our ecosystems and natural resources, due to the acceleration of urbanization and the worldwide population boom. Within this framework, this study uses ML to automate the separation of organic and non-organic trash, therefore transforming current methods of waste management [1].The pressing need to find long-term solutions to waste management that lessen trash in landfills, make better use of available resources, and lessen environmental damage is driving this study. Manual effort and human judgement are common in traditional garbage sorting procedures, although they are laborious and error-prone [2]. This study overcomes these shortcomings by analyzing and categorizing trash objects according to their content, traits, and recyclable status using ML algorithms. So far, the study has focused on building and training ML models that can differentiate between organic trash (like food scraps and yard clippings) and non-organic garbage (such plastics, metals, and glass) using inputs such as photographs, sensor data, or other sources. Municipalities, recycling centers, and individuals may all benefit from the improved sorting efficiency brought about by the automated trash categorization system.

[3]. The study also highlights the importance of technology implementation in an ethical context. The significance of using AI responsibly, protecting data privacy, and implementing sustainable waste management techniques cannot be overstated. This is necessary to guarantee that the advantages of ML-driven trash categorization do not conflict with ethical and environmental concerns [4]. This introduction summary will go into the main points and aims of this study. We will discuss the problems caused by increasing garbage production, the function of machine learning in trash categorization, and the revolutionary possibilities of this study for better waste management. We will also discuss the practical implications and ethical issues raised by this study, which have implications for sustainable urban design, recycling infrastructure, and municipal trash management [5]. The groundbreaking "ML-Driven Waste Classification for Effective Organic and Non-Organic Waste Management" [6] aims to use ML's capabilities to tackle the worldwide problem of trash management. Through the use of automated waste categorization systems, this study endeavors to improve resource recovery, lessen the negative effects on the environment, and advance sustainable practices in waste management, all while upholding ethical principles and responsibly using technology.

1.2 ResearchMotivation

The research on "ML-Driven Waste Classification for Effective Organic and Non- Organic Waste Management" is driven by a number of important reasons that highlight the pressing need for ground-breaking solutions in the field of waste management. The most important driving force is the ever-increasing volume of trash in today's society. An extraordinary boom in

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garbage generation has resulted from rapid urbanization, population expansion, and increasing consumption, pushing current waste management systems to their limits [7]. The environmental and logistical issues brought about by this rise are exacerbated by the fact that conventional garbage sorting processes are inefficient, labor-intensive, time-consuming, and error-prone. The urgent need to address the environmental consequences of waste management systems that are not efficient is what drives this study. Overflowing landfills and unregulated garbage incineration are examples of incorrect waste disposal that have serious environmental effects [8]. They exacerbate the world's environmental problem by adding to the emission of dangerous greenhouse gases, the contamination of soil and water, and the pollution of the air. The project aims to optimize waste categorization using Machine Learning (ML) technology to overcome these problems, promote sustainable waste management methods, and reduce environmental deterioration [9].

Looking for ways to maximize recycling efficiency and optimize resources is another major driving force. Materials like plastics, metals, and glass are examples of non-organic garbage. These items typically include valuable resources that may be recovered and repurposed. By automating trash sorting using machine learning, we can increase recovery rates and make it easier to incorporate these materials into the circular economy, which helps to preserve natural resources by decreasing demand for newly extracted materials. Responsible management of Earth's resources is aided by this resource-centric approach, which is in line with sustainability objectives. Responsible waste management also has an ethical component, which is a major driving force

[10]. To guarantee that the advantages of ML-driven trash categorization are in line with ethical values and ecological responsibilities, the study stresses the significance of ethical AI use, data privacy protection, and sustainable waste practices. In order to promote a more sustainable and responsible approach to waste management, the study seeks to address these ethical issues and encourage the deployment of technology in an ethical and effective manner. Addressing the challenges of increasing waste generation, reducing environmental impact, optimizing resource utilization, and upholding ethical principles in waste management practices are the driving forces behind "ML-Driven Waste Classification for Effective Organic and Non-Organic Waste Management." To promote sustainability and ethical waste management in a world facing increasing environmental issues, our project aims to use ML technology to transform garbage sorting and recycling operations.

1.3 ProblemDefinition

Modern civilization's garbage output has skyrocketed due to enormous increases in urbanization, population, and consumerism. Managing the increasing amount of garbage is a

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complex issue that goes beyond just the amount of items being dumped. Traditional waste management procedures, especially when it comes to trash categorization, have certain limits and inefficiencies, which this study aims to overcome. Traditional garbage sorting technologies are labor-intensive and prone to human mistake since they depend so much on human judgement and physical labor. The increasing variety and volume of trash, which often contains both organic and inorganic components, is posing a challenge for these systems to handle. For this reason, creating an ML-powered automated waste classification system that reliably and effectively sorts trash into organic and non-organic categories is the main obstacle. The first step is to teach machine learning algorithms to sort through different types of data (pictures, sensor readings, etc.) and identify certain types of trash based on their composition and other criteria.

personality traits. The ultimate goal is to improve resource recovery, lessen environmental damage, and increase the efficacy of waste management procedures by using data-driven automated trash categorization. By using ML's capabilities, this study tackles the crucial issue of contemporary waste management and turns waste categorization into an effective and sustainable procedure.

1.1 Significance

In place of time-consuming and error-prone human sorting, this study presents an AI-powered Intelligent Organic Recyclable Objects Categorization System that uses machine learning to automate trash categorization. Sustainable waste management practices are promoted by this approach, which also improves efficiency and decreases landfill buildup. The technology aids in responsible recycling by combining image-based categorization with Convolutional Neural Networks (CNNs), which increases sorting accuracy.

Improved Waste Classification Accuracy: Mistakes and discrepancies are common with older manual sorting techniques. The suggested convolutional neural network (CNN) classification approach assures dependable separation of organic and non-organic waste by substantially improving accuracy.

Utilizes image-based databases for trash classification, enabling improved recycling decision-making; data-driven sustainable waste management. Assists in decreasing landfill buildup by the accurate identification and processing of recyclable items.

In-Depth Exploratory Data Analysis (EDA): The research makes use of state-of-the-art visualization tools (heatmaps, bar graphs, principal component analysis, etc.) to delve further into patterns in waste composition. Makes it possible to optimize categorization algorithms and get insight into patterns in trash creation using data.

The use of inefficient and time-consuming manual labor is eliminated by automation, leading to increased efficiency. Facilitates an automated, scalable system for

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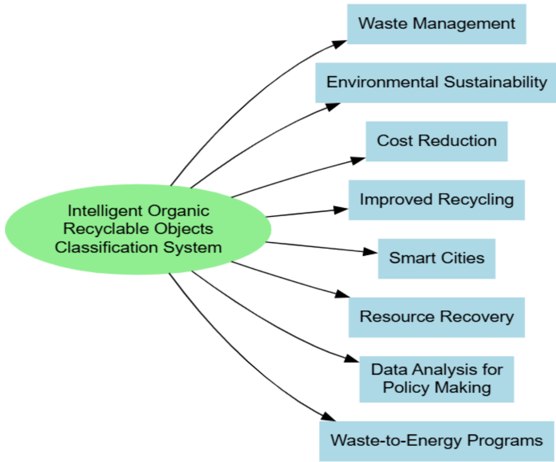
garbage categorization by decreasing the likelihood of human mistake during sorting.

The suggested method has practical uses in urban waste management, such as smart trash cans, recycling centers, and citywide trash collection initiatives. Streamlines recycling efforts and supports smart city projects via real-time garbage sorting.

Applications

- Waste Management: The principal use involves optimizing the waste segregation process, augmenting recycling rates, and diminishing the volume of garbage sent to landfills.
- Environmental Sustainability: This approach facilitates the precise classification of organic waste (suitable for composting) and non-organic trash (eligible for recycling), hence reducing environmental pollution and fostering sustainability.
- Cost Reduction: Automating the trash categorisation process reduces the need for human labour, hence decreasing operating expenses.
- Enhanced Recycling: Improved segregation of recyclables from non-recyclables results in heightened recycling rates and less pollution of recycling streams.
- Smart Cities: The integration of smart city technology may enhance the efficiency of waste management operations in urban settings.
- Resource Recovery: This method facilitates the extraction of precious resources, including metals and polymers, using enhanced sorting techniques.
- Data Analysis for Policy Formulation: The system's data may provide insights for waste management regulations, assisting policymakers in formulating more effective plans.
- Waste-to-Energy Initiatives: It may enhance waste categorization for energy generating suitability.



2. LITERATURE REVIEW

Fogarassy et al. [11] advocated for a composting strategy as an alternative to waste-to-energy in urban settings. The aim of this study is to identify the obstacles to organic waste management solutions from the standpoint of stakeholders and to examine their causal links in order to address the organic waste management issue from a systemic viewpoint. Numerous significant issues have been discovered in organic waste management systems; the present intervention summary suggests that enhancing and monitoring focus on "value to waste" would constitute a successful strategic strategy. Kharola et al. [12] presented obstacles to organic waste treatment within a circular economy. This research aims to identify the obstacles to organic waste

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management solutions from the standpoint of stakeholders and to examine their causal links in order to address the organic waste management issue from a systemic viewpoint. Numerous significant issues concerning organic waste management solutions have been discovered; the present intervention summary suggests that fostering and monitoring focus on "value to waste" would constitute a successful strategic strategy.

Loganayagi et al. [13] suggested an automated method for waste classification via deep learning. The research created a tailored inception model by including more layers and evaluates its performance in terms of accuracy against the standard Inceptionv3 model. The research used stochastic gradient descent (SGD) with a linear regression technique for classification and utilised categorical cross-entropy for loss assessment. The present research employs the ReLU function to address the challenges of underfitting and overfitting.

Mookkaiah et al. [14] suggested the design and implementation of a smart Internet of Things-based solid waste management system using computer vision. The suggested methodology categorises garbage into biodegradable and non-biodegradable types for accurate collection in designated containers. Moreover, the assessment of performance metrics, accuracy, and loss guarantees the efficacy of the proposed model in comparison to other current models. The suggested ResNet-based CNN achieves 19.08% greater accuracy and 34.97% reduced loss compared to the performance metrics of other current models in garbage categorisation.

Alvianingsih et al. [15] suggested an automated waste categorisation system using an Arduino-based controller and the binary tree idea. The suggested design has an automated door,

sorting waste, UI, and capacity controller. Arduino Mega 2560 microcontroller, HCSR04 ultrasonic sensor, MG996R servo motor, I/O proximity sensor, and CPS are the key parts of the system. Based on the results of the performance tests, we know that the HC-SR04 ultrasonic sensor makes a 33.3% mistake when stabilising distances for objects, that inductive proximity sensors are 100% effective when detecting metals, and that capacitive proximity sensors are 85.7% effective when detecting organic waste.

Modelling Organic Waste Classification as Raw Materials for Briquettes using Machine Learning was suggested by Saptadi et al. [16]. Technology, object identification, and classification were the original goals of the development of machine learning methods. The Naive Bayes Classifier is one example of an artificial reasoning network that uses many algorithms to discover and determine certain features in digital data sets. There are a number of steps in the production process that use data from a waste categorisation model.

The use of deep learning networks for the automatic categorisation of visual contaminants in textiles was suggested by Tasnim et al. [17]. Textile companies may look forward to future visual pollution ratings generated by the suggested automated categorisation system. Companies, governments, and

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employees in the manufacturing sector may all play a role in limiting the spread of visual pollution by establishing regulatory frameworks. With a training accuracy of 97% and a test accuracy of 93%, the EfficientDet framework outperformed the competition. With a significantly reduced number of epochs, the YOLOv5 method demonstrates satisfactory accuracy. In order to digitalise waste sorting management, Saptaputra et al. [18] suggested a mobile app. Starting with the selection of household garbage, this study focusses on households. Organic garbage, non-organic waste, B3 or e-waste, and sanitary waste are the four main types of waste that are sorted. An early version of the 'Pilahin' software was released with the goal of using mobile app technology to get more people to sort their home trash, particularly women. The app's popularity in metropolitan areas is a major factor in its selection for smartphone media applications. The software has a tonne of features that make it easy to scan and detect garbage, classify rubbish for easy identification and sorting, and even discover trash banks in the area.

Municipal Waste Management: Current Research and Future Challenges was offered by Hemati et al. [19]. Undeveloped nations generate between 0.4 and 0.6 kilogramme of garbage per inhabitant. But this rate ranges from 0.7 to 1.8 kilogrammes per capita in industrialised nations. Households, businesses, municipalities, industries, open spaces, treatment facilities, and farms are the usual suspects when it comes to solid waste. The specific heat capacity, organic and mineral content, water content, aggregates, and compounds of waste are the main criteria for waste identification.

The authors Madden et al. [20] put forth Calculating the amount of pollution caused by the transportation and collecting of organic waste from homes. Emissions from transport and kerbside organic waste collection in the Greater Sydney region in 2018–19 are the focus of this research. A GIS-integrated route optimisation model was used, which made use of data on property-lot garbage production and high-resolution road networks. Our model took into account the transportation of garbage to landfills and reprocessing centres, as well as the transportation of collection vehicles 'to' and 'from' transfer stations and curbside collection places across the 43 municipal regions.

Using the Eigenface approach and the Internet of Things, Wijayanto et al. [21] suggested developing a gadget that might assist in sorting organic and non-organic garbage using computer vision-based artificial intelligence technologies. Eigenface is a workaround for face recognition that relies on XML files. Testing in this system has shown promising results; when it recognises organic things, the chopping machine door opens; when it detects nonorganic materials, the door closes.

The Naive Bayes Algorithm was suggested by Fadil et al. [22] as a Waste Classifier. Finding out how well the Naïve Bayes algorithm categorises trash classifiers is the main objective of the study. The goal of this Arduino-based waste classifier is to use the naive Bayes

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method—a classification system that requires extensive training data—to distinguish between organic, inorganic, and hazardous trash. In order to search for opportunities or data training, this tool is built utilising an Arduino Uno R3, a capacitive proximity sensor, a $16\mathrm{x}2$ LCD, and a data table.

Finding the Waste Supply Chain's Structure for a Circular Economy was suggested by Nasirly et al. [23]. A qualitative technique is used in this study's descriptive methodology. Researchers at PangkalanKerinci discovered that the town's environmental service covers 72% of the town's land area with the use of 19 dumping trucks, 19 garbage collecting routes, 4 bin container trucks, and motorbikes for inaccessible areas. PangkalanKerinci's waste management issues include an absence of trash cans and banks, an absence ofworkers involved in moving and sorting materials, an absence of excavators at the landfill, and an inadequate fleet of garbage trucks and other collection vehicles.

It was suggested by Aarthi et al. [24] Finding trash cans and other items with certain geometric properties for robotic manipulation using a vision-based method. In order to facilitate recycling, a system is suggested for the automated identification and separation of waste materials in real-time. The suggested method finds and labels trash in the wild using the state-of-the-art deep learning architecture, Mask RCNN. To further assist the robotic arm in grabbing the trash item, geometric characteristics such as the object's centroid, orientation, and clamping points are retrieved.

Achmad et al. [25] put forth Waste management an Islamic viewpoint. The main objective of the research is to identify the factors that influence the level of participation of the Batu BantarGebang community in the establishment of a waste bank. This study used qualitative research methods. The research team gathered their information via in-depth interviews, careful field observations, and a perusal of pertinent scholarly literature. The research was conducted in the Ummu Amanah Foundation in Sumur Batu District, specifically at Al-Falah School in BantarGebang, Bekasi, West Java.

3. PROPOSED SYSTEMS

3.1 Overview

First Step: Gathering Soil Image Datasets This study's first and most important phase comprises the

assembly of an extensive database including pictures of dirt. Soil kinds are shown below, and they may be roughly grouped into two groups: organic and nonorganic. The dataset may be derived from a variety of sources, including open-source databases, field studies, or specialized high-resolution camera images. Model accuracy is directly affected by correct dataset labelling, which is why it is of the utmost importance at this point. After the photographs are gathered, they are placed into specific folders according to the labels assigned to them. Dataset augmentation methods like flipping, rotating, and brightness modifications may be used to artificially enlarge and diversify

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datasets, which is necessary for machine learning and deep learning models to generalize successfully.

Step 2: Processing the Images (Standardization and Normalization)

Important preprocessing follows dataset collection. The models' ability to learn may be impacted by the changes in brightness, contrast, and resolution seen in raw photos. All photos are reduced to 64x64 pixels for consistency's sake. This is a standard size thatstrikes a compromise between accurately representing features and maximizing computing efficiency. Next, we normalize the images by reducing the pixel values to a range of 0 to 1. This makes it easier for neural networks to train without experiencing huge numerical fluctuations. To further improve the photographs' quality, one may use filtering methods and color channel modifications. To make them work with machine learning methods, the preprocessed photos are transformed into NumPy arrays. Also, during model construction, the processed pictures are stored into cache files (such NPY and Y.npy) so that they may be loaded and trained quicker.

Thirdly, use the current model's Extra Trees Classifier (ETC) to sort soil types.

The Extra Trees Classifier (ETC), an ensemble learning approach based on multiple decision trees, is used as the baseline model for comparison in this study. To train the ETC model, the soil pictures are preprocessed by first reducing them to one-dimensional feature vectors, which are then inputted into the classifier. To overcome overfitting and increase accuracy, the Extra Trees Classifier constructs a number of independent decision trees and then averages their predictions. An effective and resilient approach for structured data categorization, it conducts substantial tree splitting and randomly chooses features. While developing the model

during training, with 80% of the dataset going into the training process and 20% going into testing to gauge generalizability. To facilitate future use without retraining, the learnt model is stored in a serialized format (ETC_model.pkl). The accuracy, precision, recall, F1-score, and confusion matrix analysis are some of the common classification metrics used to evaluate its performance. Deep learning outperforms ETC, a powerful classical machine learning method, when it comes to collecting complicatedspatial characteristics in photos. Phase 4: I propose a model for soil classification using a convolutional neural network (CNN). An improved categorisation algorithm that uses deep learning

Technique that makes use of a CNN. Convolutional neural networks (CNNs) automatically learn spatial feature hierarchies from raw pictures, making them ideal for picture categorisation applications. The suggested convolutional neural network (CNN) design includes:

The input layer can handle RGB channels with a size of 64x64x3.

- Using ReLU activation to induce non-linearity, 32 filters (3x3 kernel) are used to extract features in convolutional layers.

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- Using max-pooling layers, spatial dimensions are reduced by the use of 2x2 pooling, resulting in efficient calculations.

- A flattening layer is used to transform feature maps from several dimensions into a vector with just one dimension.

  To improve learning ability, fully connected layers use ReLU activation on 256 neurones.

- Layer of Output: Classifies objects into two groups, "Organic" and "Nonorganic," using a SoftMax activation function.

  Using a learning rate of 0.001 and a categorical cross-entropy loss function, the model is trained using the Adam optimizer. You can find the model's architecture in DLmodel.json and the learnt weights in DLmodel_weights.h5, after 20 epochs of training with a batch size of 16. Data augmentation methods are used to guarantee robustness, including horizontal flipping and brightness modifications. Next, the convolutional neural network (CNN) model is assessed using confusion matrices, F1-score, recall, accuracy, and precision, same as the ETC model. Fifth Step: Evaluate Results We compare the suggested CNN model's performance to that of the classic Extra Trees Classifier in order to prove that it is superior. Important criteria including specificity, accuracy, sensitivity, and the confusion matrix form the basis of the assessment. In every case, the CNN model proves to be more accurate and resilient than the Extra Trees Classifier.

- Because it learns spatial relationships in pictures more rapidly, the CNN model attains a much greater accuracy rate than the ETC model.

- Recall and Precision: Convolutional Neural Networks (CNNs) provide higher recall and precision scores, which means they reduce the incidence of false positives and false negatives.

- Problems with F1-Score When comparing CNN with the ETC model, the former excels in classifying both organic and nonorganic data, while the latter has difficulty with more complicated characteristics (matrix analysis).

- Data visualization: Overfitting is not an issue when using CNN, as shown by the training loss and validation accuracy graphs.

3.1 Datasplitting&imagepre-processing

For this study's model training and assessment to be successful, data partitioning and picture preprocessing are vital. Soil photos are initially split into two primary subsets, the Training Set and the Testing Set. The Training Set contains 80% of the photographs while the Testing Set has 20%. For an objective evaluation of the model's generalizability, this typical split makes sure it learns from a large chunk of the dataset while simultaneously being tested on unknown data. While the testing set is utilized to evaluate classification performance independently, the training set is used to optimize the model parameters. Improving picture quality and standardizing raw data is the next stage after data splitting, which is image preparation.

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When training, discrepancies may arise because to the raw soil photos' varying resolutions, brightness, contrasts, and background noise.

The solution is to scale all the photographs to the same 64x64 pixel size so that the dataset is consistent. Furthermore, pixel values are scaled between 0 and 1 to apply normalization. After the preprocessing is finished, the photos are saved as NumPy arrays so they may be loaded efficiently while the model is being trained. All of these things work together to make sure the dataset is ready for accurate classification using ML (Extra Trees Classifier) and CNN (deep neural network) models.

3.2 ModelBuilding

One of the most important parts of this study is the model development phase, wherein two soil image classification algorithms, one based on the existing Extra Trees Classifier (ETC) algorithm and the other on the proposed Convolutional Neural Network (CNN) algorithm, are created. While the CNN model uses deep learning to extract hierarchical spatial characteristics from photos, the ETC model uses machine learning to create multiple decision trees for soil image classification. To find out which method is better, we compare the two models' performances after training them on the same preprocessed dataset. The increased feature extraction capabilities of the CNN model are anticipated to lead to greater accuracy.

HowCNNWorks?

1. In order to extract features, the model uses convolutional filters on the input pictures.
2. distinct soil properties are located by use of feature maps.
3. Layers that use MaxPoolingminimise dimensionality while preserving key characteristics.
4. Fully linked layers are responsible for learning relationships and interpreting retrieved characteristics.
5. To sort photos into different folders, the output layer employs Softmax activation.

4. RESULTS

Figure 9.1 shows a Tkinter-based GUI designed for an AI-driven system that classifies recyclable objects as "Organic" or "Nonorganic" to aid in landfill minimization. The interface features buttons for key functions such as dataset uploading, image processing, dataset splitting, training classifiers (ExtraTrees and CNN), making predictions, and displaying accuracy/loss graphs. The loaded dataset includes two classes, "Organic" and "Nonorganic," as displayed in the text box. The left-side panel consists of buttons for user interaction, while the right side provides real-time updates on dataset status and model progress. The output message "Dataset loaded" confirms that the dataset has been successfully uploaded into the system. The next line, "Classes found in dataset: ['Nonorganic', 'Organic']", indicates that the dataset consists of two categories: "Nonorganic" and "Organic," meaning the AI model will classify recyclable objects into these two groups. This classification helps in waste management and landfill minimization.

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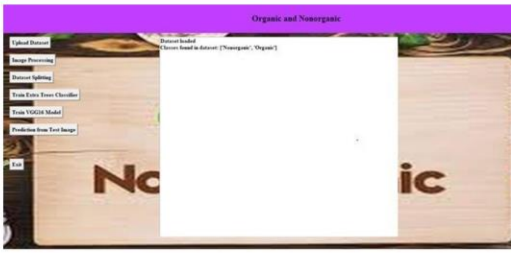

Figure9.1:GUI of Organic and Nonorganic

Figure9.2:After Data Splitting

Figure 9.2 shows that dataset pre-processing is complete, with the training dataset containing 2,339 samples and the testing dataset containing 585 samples, each represented as a 12,288- dimensional feature vector. This indicates that the images have been transformed into numerical representations, likely through feature extraction, to prepare them for training andevaluation in the AI model.

Comparative Analysis

Table.1 Performance Comparison of Various Algorithms Performance Comparison Table: Existing ETC vs. Proposed VGG16

Metric	ExistingETC	ProposedVGG16
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 clearlydemonstrate 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 correctnessofpositivepredictions,isalso notablyhigherintheVGG16modelat97.60%, 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 ExtraTrees Classifier.

Table.2PerformanceMetricsofexisting ETC

Metric	ExistingETC
Accur	76.23%

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acy	
Precision	76.51%
Recall	76.35%
F1-Score	76.22%

6. CONCLUSION

To help reduce trash in landfills, this research created an AI-driven system using Tkinter to sort recyclables into "Organic" and "Nonorganic" piles. Extra Trees Classifier (ETC) and Convolutional Neural Networks (CNN) are two classification models that are included into the system to evaluate how well they classify objects. By all measures (accuracy, precision, recall, and F1-score), the CNN model proves to be much superior than the ETC model. The CNN model's remarkable accuracy of 97.78% shows that it can extract useful features and boost classification performance, in contrast to the ETC model's 76.24%. The CNN model's confusion matrix shows that it is quite resilient, with many fewer misclassified examples than the ETC model. To facilitate its implementation in real-world waste management applications, the system's graphical user interface (GUI) offers a user-friendly and interactive setting for managing datasets, training models, and classifying data. This AI-driven method may help the environment by automating the categorization of recyclable items, which saves time and effort for humans while increasing recycling efficiency.

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