

ML-DRIVEN WASTE CLASSIFICATION FOR EFFECTIVE ORGANIC AND NON-ORGANIC WASTE MANAGEMENT

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ABSTRACT

A Smart Waste Collection system can be enhanced by optimizing waste collection routes through real-time waste classification, thereby reducing operational costs. Accurate waste classification promotes efficient recycling by directing organic waste towards composting and converting non-organic waste into recyclable materials. This proper classification prevents the contamination of soil, water, and air, mitigating the environmental impacts of improper waste management. Segregating organic waste for composting returns valuable nutrients to the soil, supports sustainable agriculture, and conserves resources. Traditional waste classification methods, which often rely on manual sorting or basic rule-based systems, are labor-intensive, time-consuming, and prone to errors. Human involvement can lead to inconsistencies and variations in waste categorization, while rule-based systems struggle with complex and diverse waste compositions, resulting in suboptimal accuracy, particularly with mixed waste. These methods may also lack scalability and adaptability for large-scale urban waste classification. In contrast, a machine learning (ML)-driven waste classification system harnesses AI algorithms to automate and enhance the classification process. By employing image analysis techniques to extract visual features such as color, texture, and shape from waste images, the system achieves higher accuracy and efficiency in waste classification.

Keywords: Smart Waste Collection, Real-Time Waste Classification, Machine Learning, Environmental Sustainability, Recycling Efficiency, Automated Waste Sorting

1. INTRODUCTION

The research topic, ML-Driven Waste Classification for Effective Organic and Non-Organic Waste Management, stands at the forefront of addressing one of the world's pressing environmental challenges: efficient waste management. 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 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]. 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 [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.The research on "ML-Driven Waste Classification for Effective Organic and Non-Organic Waste Management" is motivated by a confluence of critical factors that underscore the urgent need for transformative solutions in waste management practices. First and foremost, the escalating magnitude of waste generation in our modern world serves as a compelling motivation. Rapid urbanization, population growth, and increased consumption have led to an unprecedented surge in waste production, straining existing waste management systems to their limits [7]. This surge not only poses environmental and logistical challenges but also highlights the inefficiency of traditional waste sorting methods, which are often labour-intensive, time-consuming, and prone to errors. Moreover, the pressing environmental impact of inefficient waste management practices propels this research. The environmental consequences of improper waste disposal, including overflowing landfills and uncontrolled waste incineration, are profound [8]. They contribute to the release of harmful greenhouse gases, soil and water contamination, and air pollution, thus exacerbating the global environmental crisis. The research seeks to address these challenges by harnessing Machine Learning (ML) technology to optimize waste classification, with the aim of reducing environmental degradation and promoting sustainable waste management practices [9]. Another significant motivation lies in the quest for resource optimization and recycling efficiency. Non-organic waste, which includes materials such as plastics, metals, and glass, often contains valuable resources that can be reclaimed and reused. Effective waste classification through ML-driven automation not only improves the recovery of these resources but also facilitates their integration into the circular economy, reducing the need for virgin resource extraction and conserving natural resources. This resource-centric approach aligns with sustainability goals and contributes to the responsible stewardship of our planet's resources. Furthermore, the ethical dimension of responsible waste management is a central motivation [10].

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 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.

3. PROPOSED SYSTEM

This research focuses on image classification, specifically distinguishing between organic and non-organic objects. It begins with image preprocessing to prepare the data, followed by dataset splitting to create training and testing subsets. The CNN is chosen as the classification model, and it undergoes thorough examination for accuracy, precision, recall, and overall readiness for deployment. This project's goal is to create a robust image classification model capable of accurately identifying organic and non-organic objects, with potential applications in fields such as agriculture, waste management, and environmental monitoring. Figure 4.1 shows the proposed system model. The detailed operation illustrated as follows:

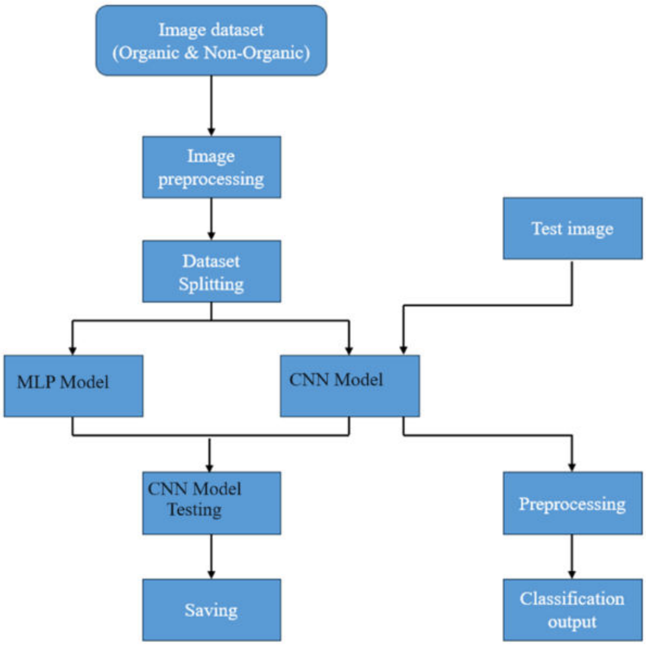

Figure 1. Proposed System model.

step 1: Image Preprocessing: The project begins by collecting an extensive range of images that contain both organic and non-organic objects. Image preprocessing is the initial step, where the collected images undergo various transformations and enhancements to prepare them for analysis. Preprocessing steps may include resizing, cropping, color normalization, and noise reduction.

step 2: Dataset Splitting: After preprocessing the images, the dataset is divided into two subsets: a training set and a testing set. The common split ratio is 80% for training and 20% for testing. This division ensures that the model is trained on a substantial portion of the data while also reserving a separate portion for evaluating its performance.

step 3: MLP Training Model:

- A MLP model is chosen for the image classification task. MLP is known for its versatility and effectiveness in handling image data.
- The training phase involves feeding the preprocessed images from the training set into the MLP model. During this process, the model learns patterns and features that distinguish organic and non-organic objects. It aims to create a decision boundary that can accurately classify images based on their content.

step 4: Model Examination: After training, the CNN model is subjected to a comprehensive examination to assess its performance in classifying organic and non-organic images. This evaluation typically includes several key aspects:

- **Accuracy**: This metric measures the percentage of correctly classified images out of the total number of images in the testing set. It provides an overall assessment of how well the model is performing.

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- **Precision**: Precision measures the proportion of true positive predictions (correctly classified organic images) out of all the positive predictions (organic images). It quantifies the model's ability to avoid false positives.
- **Recall (Sensitivity)**: Recall calculates the proportion of true positive predictions out of all actual organic images in the testing set. It reflects the model's ability to detect organic objects accurately.
- **F1-Score**: The F1-Score is the harmonic mean of precision and recall. It offers a balanced assessment of the model's performance, especially when class distribution is imbalanced.

Convolution Neural Network

According to the facts, training and testing of CNN involves in allowing every source data via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from.

Convolution layer is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here d=3 since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$..

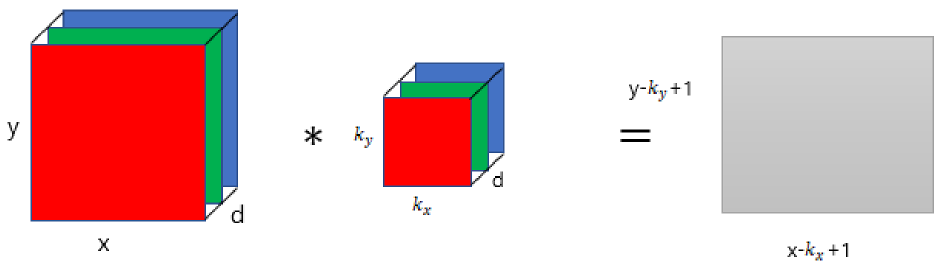

Fig. 2: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), (y - k_y + 1), 1\right)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.

1	1	1	0	0
0	0	1	1	1
1	1	0	0	1
0	0	0	1	1
1	1	1	0	0

5x5 image

*

1	0	1
0	1	0
1	0	1

3x3 kernel

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(a)

$$\underset{\text{5x5 image}}{\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 0 & 0 \end{bmatrix}} * \underset{\text{3x3 kernel}}{\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}} = \underset{\text{Feature map}}{\begin{bmatrix} 3 & 3 & 3 \\ 2 & 2 & 3 \\ 3 & 2 & 3 \end{bmatrix}}$$

(b)

Fig. 3: Example of convolution layer process (a) an image with size 5×5 is convolving with 3×3 kernel (b) Convolved feature map.

ReLU layer

Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

Max pooing layer

This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

Advantages of proposed system

- CNNs do not require human supervision for the task of identifying important features.
- They are very accurate at image recognition and classification.
- Weight sharing is another major advantage of CNNs.
- Convolutional neural networks also minimize computation in comparison with a regular neural network.
- CNNs make use of the same knowledge across all image locations.

4. RESULTS AND DISCUSSION

This figure showcases the initial step in the waste classification process, where a sample dataset is uploaded into the Waste Classification Graphical User Interface (GUI). The GUI provides an intuitive platform for users to interact with the dataset, enabling them to visualize, analyze, and preprocess the data effectively before model training.

Figure 5: Upload of Sample dataset in the Waste Classification GUI.

A count plot displayed in this figure illustrates the distribution of classes within the target column of the dataset. This visualization provides valuable insights into the class distribution, which is crucial for understanding potential class imbalances. It allows users to identify whether certain classes are overrepresented or underrepresented, guiding decisions on data preprocessing strategies and model evaluation techniques.

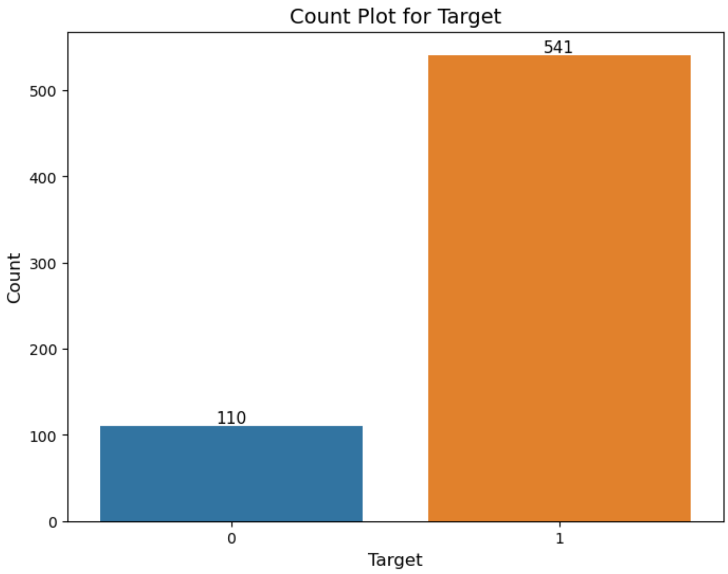

Figure 6: Count plot for target column in a dataset.

The figure presents a data frame containing image data after undergoing preprocessing steps. Preprocessing involves operations such as resizing, normalization, and augmentation to standardize the images and enhance their suitability for model training. This data frame serves as a snapshot of the processed image data, facilitating further analysis and model development.

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Figure 7: Data frame of image data after preprocessing

A heatmap depicting the confusion matrix for the Multilayer Perceptron (MLP) model is shown in this figure. The confusion matrix provides a comprehensive overview of the model's performance by visualizing true positive, true negative, false positive, and false negative predictions. The heatmap visualization enables quick identification of misclassifications and errors made by the MLP model, aiding in diagnosing its strengths and weaknesses.

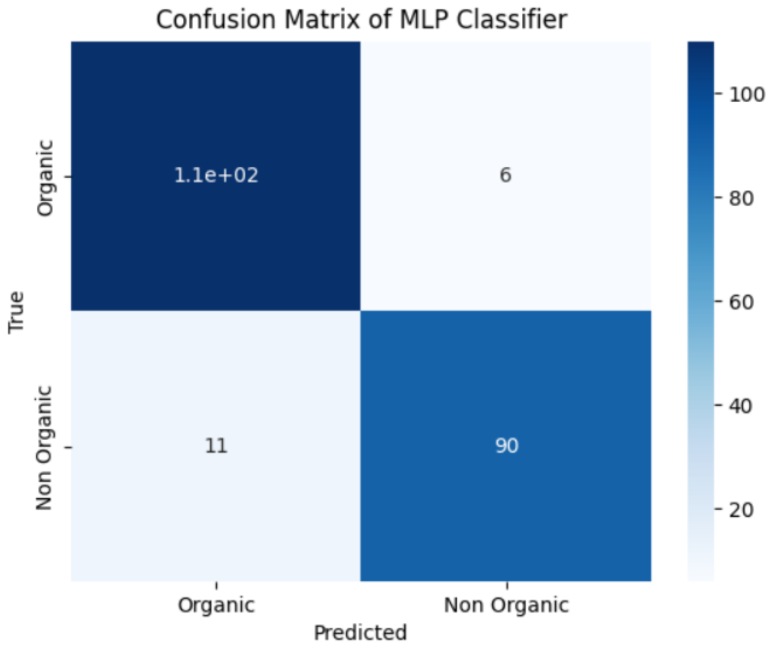

Figure 8: Heatmap of confusion matrix for MLP.

This figure displays a heatmap of the confusion matrix specifically for the Convolutional Neural Network (CNN) model. The heatmap offers insights into the CNN model's performance, allowing comparison with the MLP model's confusion matrix. It helps stakeholders understand how well the CNN model distinguishes between different classes and where it may require improvement.

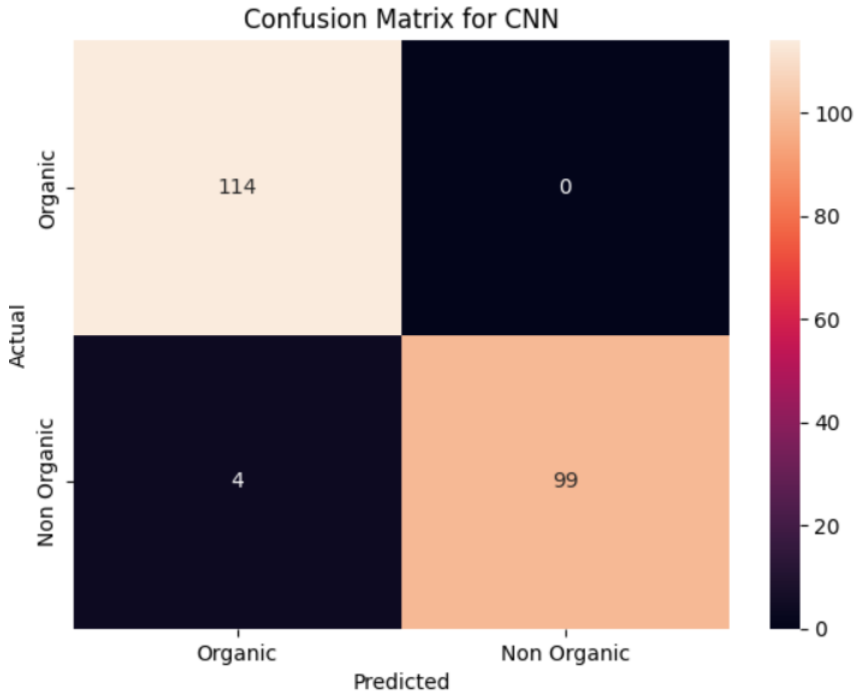

Figure 9: Heatmap of confusion matrix for CNN.

This figure illustrates the performance metrics of the CNN model across multiple epochs during training. Metrics such as accuracy, loss, precision, recall, and F1-score be plotted over epochs to track the model's training progress and convergence. Analyzing performance per epoch helps in monitoring model stability, identifying overfitting or underfitting, and fine-tuning model hyperparameters.

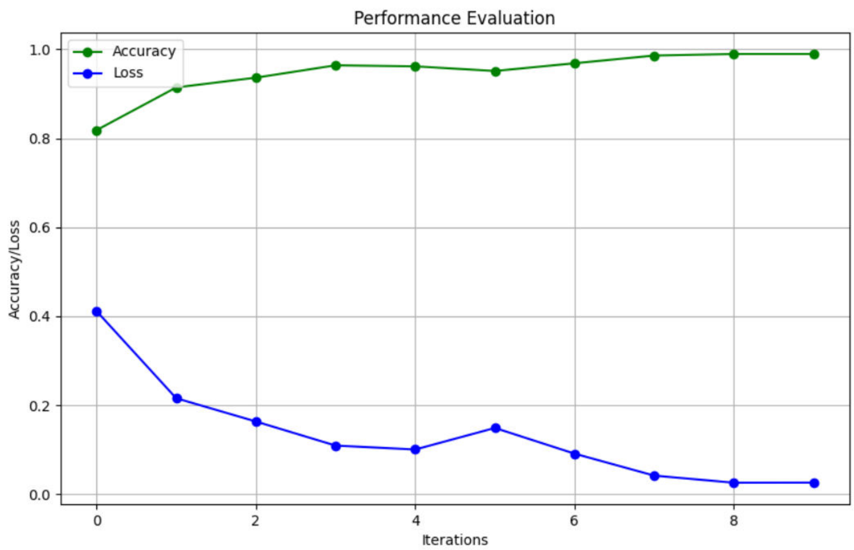

Figure 10: Performance evaluation of CNN model Per Epoch.

The figure showcases the prediction results generated by the CNN model on test data. Visualizing predicted versus actual labels allows for a qualitative assessment of the model's performance. It provides insights into areas of successful classification as well as instances

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where the model may struggle, informing potential areas for further model refinement or data enhancement.

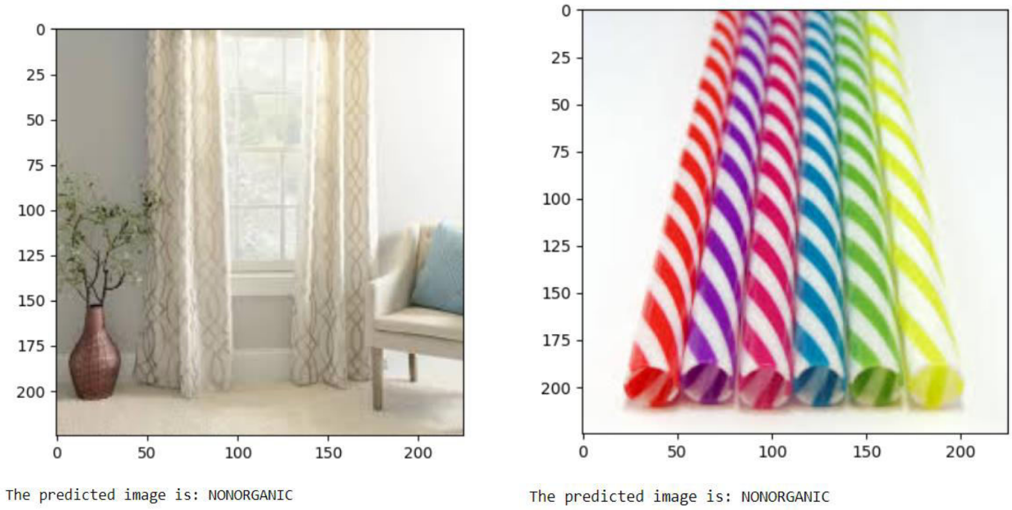

Figure 11: Prediction results on test data using CNN.

Table 1: Performance Metrics Comparison of MLP Classifier and Deep Learning Model

Metric	MLP Classifier	Deep Learning Model
Accuracy	92.17%	98.96%
Precision	92.33%	98.31%
Recall	91.97%	98.06%
F1-Score	92.10%	98.15%

5. CONCLUSION

The research, Image Classification for Organic and Non-Organic Objects, has successfully demonstrated a systematic workflow for differentiating between organic and non-organic images. Beginning with extensive data collection and image preprocessing, the project prepared the dataset for model training and evaluation. The dataset was thoughtfully divided into a training set and a testing set, with an 80-20 split ratio. A CNN was employed to train on the preprocessed images, learning to distinguish between organic and non-organic objects based on image features. Model examination yielded insights into its performance, with accuracy, precision, recall, and the F1-score providing comprehensive metrics for evaluation. This project signifies a crucial step in automating the classification of images, with potential applications in industries such as agriculture, waste management, and environmental monitoring, where distinguishing between organic and non-organic materials is essential for decision-making and resource management.

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