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ORIGINAL PAPER

Optimizing solid waste classification using deep learning and grey wolf optimizer for recycling efficiency

Y. Eryeşil[1] · H. Kahramanli Örnek[1] · Ş. Taşdemir[1]

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Abstract

Solid waste management is important for environmental sustainability. Correct classification of recyclable materials plays a critical role in increasing the efficiency of recycling processes. In our research, hyperparameters of the EfficientNet model were optimized with Grey Wolf Optimizer (GWO) to increase this efficiency. In addition to hyperparameter optimization, the performance of machine learning algorithms such as Naive Bayes, Logistic Regression, and Multilayer Perceptron (MLP) was evaluated. Furthermore, the effect of these algorithms on the classification of features extracted from different deep learning models, including EfficientNet, MobileNet, and VGG, was investigated. The EfficientNet model optimized with GWO achieved the best performance with a 95.43% accuracy rate. These results showed that hyperparameter optimization applied to deep learning models increased the success in the solid waste classification problem. The integration of deep learning-based feature extraction and the optimization ability of GWO increased the classification performance while making the training process more efficient. Furthermore, proper hyperparameter tweaking enhanced the model's overall performance by preventing overfitting. To sum up, this study shows how deep learning and optimization techniques work well in the waste management industry. The findings show that these technologies can provide significant improvements in recycling processes. Moreover, these methods have the potential to contribute to more efficient and sustainable management of recycling processes in real-world applications.

Keywords Deep learning · Feature extraction · GWO · Machine learning hyperparameter optimization · Solid waste management

Introduction

Solid waste is basically produced by human activities. Solid waste is defined as solid materials subjected to waste management. The most important types of solid waste include domestic waste (packaging materials, paper, plastic, glass, etc. and industrial waste (waste generated from production processes) (Suthar and Singh 2015). Recently, solid waste has been growing. The main factors behind this trend are the steeply growing global population, growing urbanization, altered consumption habits, and rapid industrialization (Rajput et al. 2009). The environmental impacts of solid waste are manifested through contamination of water, soil, and air (Abubakar et al. 2022).

Operations such as waste collection, transportation, treatment, disposal, and recycling are all part of solid waste management (Tchobanoglous 2009). Proper waste management is of great importance for both environmental protection and the optimal use of resources; therefore, effective management of these processes is essential to achieve good environmental health. The performance of solid waste management is greatly influenced by the correct and efficient waste classification. Effective and efficient waste separation considers the type of waste being discarded, and can facilitate recycling and reuse processes, thereby generating significant environmental and economic benefits. By appropriately separating paper, plastic, glass, and metal, these materials can

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✉ Y. Eryeşil
yusuf.eryesil@selcuk.edu.tr

H. Kahramanli Örnek
hkahramanli@selcuk.edu.tr

Ş. Taşdemir
stasdemir@selcuk.edu.tr

[1] Computer Engineering Department, Technology Faculty, Selcuk University, Konya, Turkey

be reprocessed in recycling facilities and reintroduced into the market as new products. The separation of recyclable materials from the general waste stream and their reprocessing minimizes the need for raw material extraction. In this way, it promotes the conservation of natural resources, saves energy and water, and reduces the ecological damage caused by waste. Consequently, this leads to significant environmental and economic benefits (Ghisellini et al. 2016).

Accurate waste sorting is also a key enabler of long-term environmental goals, such as reducing pollution levels, conserving non-renewable resources, and mitigating the effects of climate change (Hannan et al. 2020). With the increasingly complex demands of modern waste treatment, the need for research into new and effective classification approaches has become increasingly urgent (Kaza et al. 2018). Traditional waste classification methods are frequently not reached by conventional garbage sorting techniques, which mostly rely on manual labor and are prone to errors. Thus, it is crucial to create and put into practice new waste management system strategies that are less damaging to the environment and more effective (Olawade et al. 2024).

Significant advancements in the automatic classification of solid waste have been made possible by recent developments in AI, especially in the areas of computer vision and deep learning. Convolutional Neural Networks (CNNs), one type of deep learning algorithm, can evaluate waste material photos and learn discriminative features to accurately distinguish between various waste categories (Olawade et al. 2024). These models are trained on large, labeled datasets and can outperform traditional manual sorting in both speed and reliability. AI-based classification models combined with sensors, cameras, and robotic arms enable automated systems to continuously separate waste materials (such as plastic, glass, paper, and metal) without the need for human intervention, lowering labor costs and error rates (Cekerovski et al. 2024). Furthermore, adaptive and self-improving waste classification systems that increase in accuracy over time are made possible by machine learning models' capacity for continuous learning (Sami et al. 2020). Such AI-driven approaches contribute to more efficient recycling processes and align with environmental goals by promoting resource recovery and reducing dependence on landfills (Kaur et al. 2024).

The majority of today's solid waste classification systems rely on mechanical, manual, or basic automated techniques. Despite offering a certain level of operational efficiency, these methods have several practical and environmental drawbacks. One of the most popular traditional methods is manual sorting, in which employees physically divide waste into multiple bins (Sousa et al. 2019). Although manual sorting is an inexpensive and straightforward method, it suffers from many limitations, including a high error rate and low efficiency. Due to human uncertainty, improper segregation of hazardous materials or incorrect sorting of recyclable waste often occurs (Waste 1998). Furthermore, every stage of this procedure has the potential to seriously endanger the workers' health and safety. In contrast, mechanical sorting relies on the waste's physical attributes, such as its size, density, and magnetic qualities. This method makes use of mechanical equipment like air classifiers, screens, conveyor belts, and magnetic separators (Vaško 2015). Although mechanical sorting is more efficient than manual sorting, it may not be adequate for handling complex or heterogeneous waste streams (Yasin and Koklu 2023). Moreover, these operations usually result in high energy consumption and may not be effective in properly distinguishing certain types of waste (Rahman et al. 2014). These problems can be effectively and economically solved with the use of artificial intelligence (AI) techniques. To come up with creative answers in this situation, researchers are increasingly looking to computer science. AI-based systems can accurately analyze and categorize waste, surpassing traditional methods and advancing the creation of more intelligent and sustainable waste management ideas (Andeobu et al. 2022).

The classification of solid waste has been the subject of many studies in the literature. To categorize and examine waste data, researchers have used a variety of machine learning algorithms and deep learning models. Some of the most well-known studies on the classification of solid waste are covered below.

In 2020, Zhuang, Kang et al. (2020) developed a deep learning-based automatic waste classification system to improve the efficiency of waste collection processes. The researchers collected 4,168 images from both online and real-world sources, classifying them as recyclable or non-recyclable. Three key modifications were made to the ResNet34 architecture, which formed the basis of the classification model: multi-feature fusion at the input level, enhanced feature reuse in the residual units, and the development of a novel activation function based on a combination of Softplus, Softsign, and Swish formulations. A 99.6% performance accuracy on the constructed dataset was attained as a result of these improvements, which also increased convergence speed and classification accuracy. With an average processing time of 0.95 s per item, the study also demonstrated real-time classification capabilities by integrating the model into a smart trash can prototype that was powered by a Raspberry Pi board and solar energy. This study is an example of how deep learning architectures can greatly improve the speed and precision of solid waste classification when customized and integrated into intelligent hardware systems.

In 2021, Gupta et al. (2022) proposed a deep learning-based hardware solution to address the major urban challenges of waste detection and disposal. The system, named SmartBin, classifies waste into biodegradable and non-biodegradable categories using four pre-trained CNN models:

AlexNet, ResNet, VGG16, and InceptionNet. Three preexisting datasets—TrashNet, Waste Classification, and Drinking Waste Classification—were combined to create the training data, which included 9,606 images and seven classes. With an accuracy of 97.95% and a loss value of 0.22 on the training set, AlexNet outperformed the other models. A PiCam combined with a Raspberry Pi module serves as the foundation for the SmartBin system, which takes and recognizes pictures of waste. After classification, a servomotor in the system moves the waste to the proper bin. This integrated approach offers a practical, accurate, and efficient way to classify and dispose of waste in urban settings by fusing hardware components with pre-trained deep learning models.

In 2022, Zhichao Chen et al. (2022) introduced a new waste classification model called GCNet, which aims to improve the performance of waste classification systems through the integration of deep learning and ShuffleNet v2 architectures. Applications with limited hardware resources guided the design of this model. To improve feature extraction and generalization, GCNet, based on the ShuffleNet v2 architecture, uses new activation functions, parallel attention mechanisms, and transfer learning techniques. A dataset aligned with Shanghai's waste classification standards was created for model training. With 4,256 photos, the dataset is split into four main categories: dry waste, hazardous waste, wet waste, and recyclable waste, along with fourteen subcategories. The photos, showing various settings and backgrounds, were collected from both offline and online sources. The results indicated that on the customized dataset, GCNet achieved a classification accuracy of 97.9%. The model also demonstrated high efficiency, with an inference time of about 105 ms per prediction on a Raspberry Pi 4B, and it is compact, with only 1.3 million parameters. This study shows how lightweight deep learning models can classify waste in resource-limited environments without sacrificing efficiency or accuracy.

In 2022, Md. Wahidur Rahman et al. (2022) conducted a study aimed at enhancing waste management systems through the integration of the Internet of Things (IoT) and deep learning. A CNN-based waste classification model and smart garbage cans with multiple sensors were discussed in the study. The proposed system could monitor and manage waste in real time by using Bluetooth and IoT technologies. The accuracy of the AI model, after training on the TrashNet dataset, was 95.31%. In addition, the System Usability Scale (SUS) score of 86% showed a high level of user acceptance for the system. The authors claim that this real-time waste monitoring and management system greatly improves the overall waste management process. By combining deep learning and IoT connectivity, the system offers promise for more efficient, reliable, and practical waste management solutions.

In 2023, Shoufeng Jin et al. (2023) presented a new computer vision system based on deep learning to promote sustainable waste recycling. The proposed approach integrated attention mechanisms into the MobileNetV2 model and reduced dimensionality using Principal Component Analysis (PCA). The model was specifically designed for real-time applications on end-user devices. The model showed 90.7% accuracy for waste classification on the Huawei Cloud dataset, with a median inference time of 600 ms on a Raspberry Pi 4B microprocessor. Furthermore, in tests of actual waste identification, the system's average classification accuracy was 89.26%. This work shows how scalable and practical waste recycling applications can be implemented in real-world contexts using efficient and lightweight deep learning architectures, such as MobileNetV2 networks with attention mechanisms added.

In 2024, Md. Mosarrof Hossen et al. (2024) proposed a deep learning-based model for automatic waste separation to support urban waste treatment. The work presented an unsupervised multi-stage machine learning approach applied to the 25,000-image Garbage In, Garbage Out (GIGO) dataset. It introduced a model for automatic waste classification using modern deep learning methods. The Garbage Classifier Deep Neural Network (GCDN-Net) was the trained model used for both single-label and multi-label classification tasks. In the multi-label classification, the model detected one or more waste categories within a single image. In the single-label classification, it distinguished between waste and non-waste photos. GCDN-Net achieved an accuracy of 95.77%, precision of 95.78%, recall of 95.77%, F1-score of 95.77%, and specificity of 95.54% in the trash picture categorization test. For multi-label classification, the model obtained an F1-score of 75.01% and a mean average precision (mAP) of 0.69. Score-CAM visualizations were used to provide insights into the model's decision-making process, further validating its strength. These results demonstrate how effectively deep learning models classify waste and highlight their potential to create fully automated waste management systems, which offer real benefits in terms of accuracy and reliability.

Waste classification systems face several common challenges, including insufficient datasets, high hardware requirements, and performance limitations in real-time applications. Moreover, models designed to operate on low-resource hardware often experience decreased performance (Pitakaso et al. 2024). Addressing these challenges through hyperparameter optimization can reduce training time, maximize hardware resource utilization, and improve performance in real-time scenarios. Therefore, hyperparameter optimization represents an essential approach for enhancing the overall effectiveness of waste classification systems (Khan et al. 2022).

This study suggests a hybrid classification framework that blends deep learning-based feature extraction with metaheuristic hyperparameter optimization in response to the drawbacks noted in earlier research, including restricted hyperparameter exploration, dependence on fixed deep learning architectures, and the lack of comparative feature evaluations. In particular, traditional machine learning classifiers were used to systematically evaluate the relative discriminative capabilities of features taken from three popular CNN architectures (EfficientNetB1, MobileNet, and VGG16). In order to improve its end-to-end classification performance, EfficientNetB1 was further optimized using the GWO in light of these analyses. By methodically examining feature extractor performance and proving that metaheuristic optimization works well for increasing classification accuracy for automated waste sorting applications, this study advances the field overall.

Materials and methods

This study automated the classification of solid waste using a range of machine learning and deep learning techniques. Initially, straightforward classification algorithms such as Logistic Regression, Naive Bayes, and MLP were employed. Deep features were then extracted from input photos using pre-trained convolutional neural network models, including EfficientNet, VGG16, and MobileNet. These high-level attributes were then used as inputs for traditional machine learning classifiers, such as Naive Bayes, Logistic Regression, and MLP, to perform the final classification (Deepa et al. 2024). Lastly, the GWO was used to optimize the EfficientNet model's initial hyperparameters. The datasets, preprocessing techniques, applied models, model training, and evaluation methods are all covered in detail in this section. Waste classification could be sped up and made less expensive with the suggested method. The primary steps in the waste classification process are depicted in Fig. 1.

Dataset

In this study, the TrashNet dataset (Yang and Thung 2016), developed by the Massachusetts Institute of Technology (MIT), was utilized for the solid waste classification task. The dataset contains 2,527 high-resolution RGB images categorized into six primary waste classes: plastic (482 images), metal (410), glass (501), paper (594), cardboard (403), and trash (137). Each class includes real-world waste

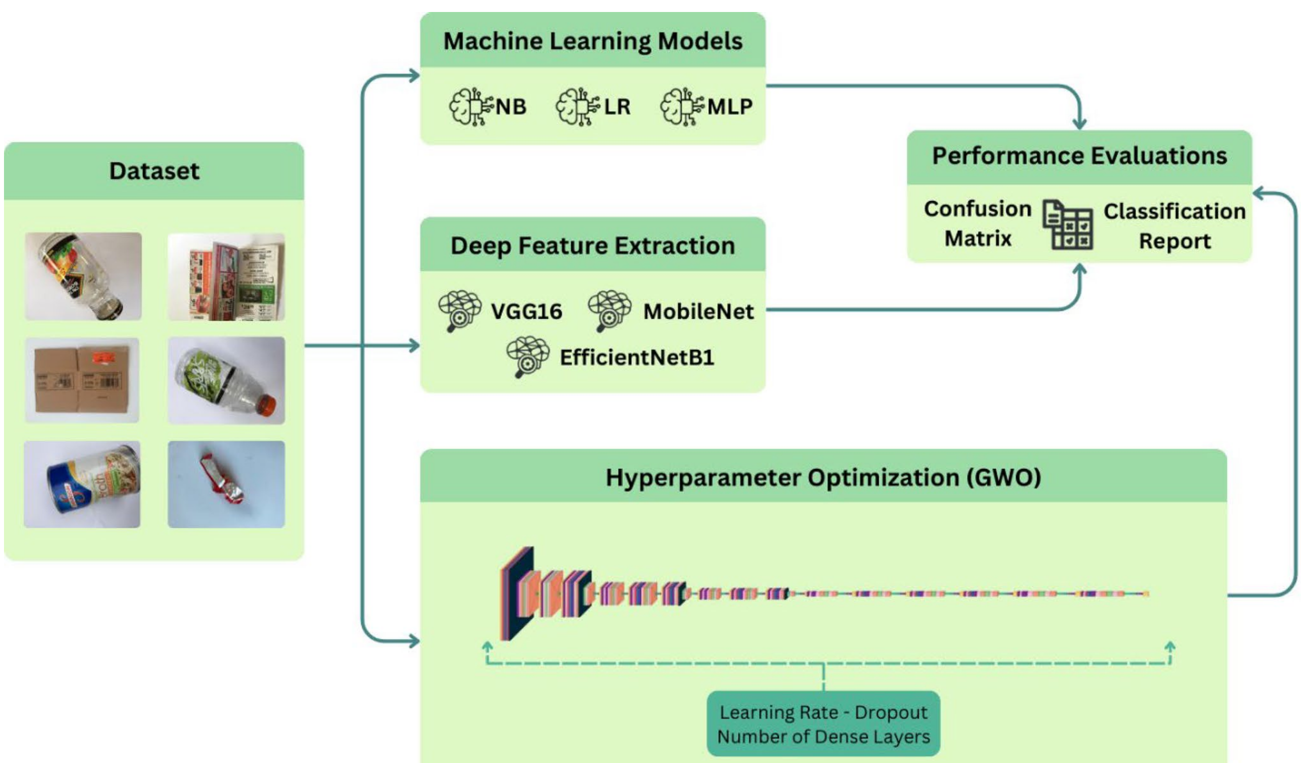


Fig. 1 Overview of the proposed solid waste classification framework. Deep features extracted via VGG16, MobileNet, and EfficientNetB1 are classified using Naive Bayes, Logistic Regression, and MLP. EfficientNetB1 is further optimized using GWO. Model performance is evaluated through a confusion matrix and classification metrics

items captured under consistent lighting and background conditions. All images were manually labeled and organized into separate folders according to their categories. The images have a resolution of 512 × 384 pixels and exhibit substantial intra-class variability, presenting a realistic challenge for classification algorithms. The TrashNet dataset has been widely used in the literature as a benchmark for training and evaluating deep learning-based waste classification models, making it a reliable foundation for comparative analysis and model development (Qin et al. 2022). Nonetheless, there is a slight class imbalance in the dataset, with fewer samples in some categories—like metal and glass. Overall accuracy metrics may be impacted by this class distribution. Despite being a widely used benchmark in waste classification research, TrashNet's fairly small size and uneven class distribution fail to capture the complexity of real-world waste, which frequently consists of visual noise, overlapping objects, and a variety of backgrounds. Future research should address these acknowledged limitations. Additionally, the dataset only represents a small geographic and cultural context, which might leave out regional differences in recycling standards or waste types. A certain amount of cultural bias in classification performance could result from this.

The dataset was divided into distinct sections based on the method used in order to guarantee a consistent assessment of both machine learning and deep learning techniques. Both the original dataset and the feature vectors obtained from deep learning models were split into 80% training and 20% testing groups for conventional machine learning algorithms. The dataset was divided into subsets of 70% training, 20% validation, and 10% testing for deep learning-based classification. Through the use of independent test data, this design guaranteed a trustworthy and equitable comparison of models. F1-score, precision, and recall metrics were used to assess the model's performance across classes. To better handle class imbalance difficulties, future research may investigate methods like class-weighted loss functions, undersampling, or oversampling.

Methods

Naïve bayes

The classification technique known as Naive Bayes is predicated on the idea of feature independence and probability theory. Using Bayes' Theorem, this model illustrates the connection between a collection of features and class labels. By maximizing P(c|x) which denotes the probability of a class c given an input x, the Naive Bayes model assigns the most probable class label c to the input. In this context, P(c|x) represents the conditional probability, that is, the probability of class c with respect to feature x (Li et al. 2014). The Bayes' Theorem, which forms the foundation of Naive Bayes classifiers, is presented in Eq. 1.

$$P(c|x) = \frac{P(x|c) \times P(c)}{P(x)} \tag{1}$$

Based on this theorem, the probability of an observation belonging to a specific class can be computed. It serves as the foundation of the Naive Bayes algorithm, enabling the model to make class predictions with high probability through probabilistic relationships between class indicators (Rish 2001).

Logistic regression

Logistic Regression is a statistical modeling approach commonly used when the dependent variable is categorical. This technique maps input features to two or more nominal outcome categories. The model estimates the log-odds of a categorical outcome as a linear combination of the independent variables and then converts this value into a probability through the sigmoid (logistic) function. (Rezaeian Zadeh et al. 2010).

Logistic Regression estimates the probability of an observation belonging to a particular class using the logistic function, as shown in Eq. 2 (Nick and Campbell 2007).

$$P(y = 1|x) = \frac{1}{1 + e^{-(b_0 + b_1 x_1 + \ldots + b_n x_n)}} \tag{2}$$

MLP

MLP is a class of artificial neural networks and serves as one of the fundamental components of deep learning models, characterized by having more than one hidden layer. MLPs are particularly well-suited for solving complex classification tasks due to their strong modeling capabilities(Foody 2004). An input layer, one or more hidden layers, and an output layer make up an MLP. Neurons that process information from the previous layer and transmit it to the next layer make up each layer. Each neuron applies an activation function to its input signals, with commonly used functions including ReLU (Rectified Linear Unit), sigmoid, and tanh (Youn and Hong 2024). The backpropagation algorithm, which updates the connection weights based on the discrepancy between the network's anticipated outputs and the actual values, is commonly used to train MLPs. The iterative nature of this process enables the model to progressively learn patterns from the training data (Karlik and Olgac 2011). In the context of solid waste classification, MLP models can effectively process a wide range of waste features, including size, shape, and color, through complex nonlinear classification functions. By summarizing these characteristics within the hidden layers and transmitting the results to the output layer, MLPs can successfully distinguish between various types of waste. Therefore, MLP represents a powerful and effective tool for waste classification tasks (Islam et al. 2014).

VGG16

One of the most widely used CNN architectures in deep learning is VGG16, which is also one of the most widely used techniques for visual feature extraction. The 16-layer model performs exceptionally well when used on large-scale image datasets. VGG16 improves performance in object and texture recognition tasks by using small convolutional kernels of size 3 × 3 to capture local features. These kernels are then combined with deep convolutional layers to increase the discriminative power of the VGG16 (Tyagi et al. 2024). After each convolutional layer, max-pooling layers are introduced to reduce the spatial dimensions of the feature maps. This process enables the network to learn generalized and abstract representations in its deeper layers (Yue et al. 2019). The architecture of VGG16 is designed to efficiently learn visual features in a hierarchical manner as information flows through successive layers, making it a valuable tool for visual data analysis and feature extraction (Patilkulkarni 2021).

MobileNet

For mobile and edge devices with constrained processing power, MobileNet is a small and effective deep learning architecture. Depthwise separable convolutions, which split the convolution process into depthwise and pointwise operations, greatly lower the computational cost of conventional convolution operations in this model (Sinha and El-Sharkawy 2019). This method preserves the capacity to extract discriminative visual characteristics while lowering the number of parameters and computing load. MobileNet is very effective for solid waste classification applications since it is especially well-suited for image-based classification and detection tasks (Abdu and Noor 2022). MobileNet significantly reduces the number of parameters and the processing cost between convolutional layers by using depthwise separable convolutions rather than conventional convolutions. It is perfect for real-time image analysis because of its lightweight architecture, which makes it possible to extract visual data quickly and effectively. The collected features offer a solid basis for further categorization models and crucial details about the waste's physical attributes, including color, shape, and size (Rabano et al. 2018).

EfficientNet

One CNN design that has gained recognition for its superior performance in image classification applications is EfficientNetB1. Classification is giving an entire image a single label based on features that have been retrieved, as opposed to recognition systems that concentrate on object detection or localization. EfficientNetB1 has been widely adopted for feature extraction and classification due to its combination of high accuracy and computational efficiency (Humayun et al. 2022). Its deep convolutional layers automatically extract hierarchical image features such as edges, textures, and color patterns, which are then combined into more abstract representations that enable effective classification. Although it does not dynamically process features at multiple scales like feature pyramid networks, EfficientNetB1 achieves robustness across varying image sizes through a compound scaling strategyThis technique balances accuracy and computing cost by equally adjusting the network's depth, width, and input resolution. Because of this, the model performs well with comparatively few parameters, which makes it appropriate for resource-efficient and large-scale image categorization applications (Failed 2024).

Grey wolf optimizer

The Grey Wolf Optimizer (GWO) is a population-based metaheuristic algorithm inspired by the leadership hierarchy and hunting strategies of grey wolves in nature (Mirjalili et al. 2014). In this study, GWO was chosen as the hyperparameter optimization method for the EfficientNetB1 model due to its ability to maintain an effective balance between exploration and exploitation during the search process. Unlike traditional approaches such as manual tuning or grid search, which are often computationally expensive and may yield suboptimal results in high-dimensional spaces, GWO dynamically adjusts candidate solutions by simulating social hierarchy and encircling behaviors among agents. This property makes it particularly suitable for addressing complex, non-convex optimization landscapes commonly encountered in deep learning applications.

The learning rate, dropout rate, and number of dense layers in the classification head are among the hyperparameters that were tuned in this work utilizing the GWO. These parameters were chosen because they have a direct impact on overfitting control, convergence speed, and model generalization. For instance, the dropout rate acts as a regularization mechanism by randomly deactivating neurons to prevent co-adaptation, the learning rate controls how quickly the model updates its weights during training, and the number of dense layers determines the final classification network's expressive capacity and depth.

Each candidate solution was encoded as a vector of these three hyperparameters, and GWO iteratively updated the search agents (wolves) based on the fitness of the best-performing solutions—alpha, beta, and delta wolves—evaluated through classification accuracy on the validation set. This process allowed the optimizer to efficiently converge toward an optimal or near-optimal configuration. The application of GWO in this context reduced training time, enhanced model performance, and improved robustness to variations in data distribution and noise levels(Cuong-Le et al. 2022; Mitra et al. 2023).

Training procedure after hyperparameter optimization

Following the hyperparameter optimization phase, the final classification model was implemented using the EfficientNetB1 architecture. The model was configured to process 224 × 224 RGB waste images, and no pre-trained weights were used during this stage. To preserve the convolutional feature extractor, the base layers were frozen, and only the classification head was trained. The architecture was enhanced by adding a Global Average Pooling 2D layer, followed by three dense layers containing 512, 256, and 128 units, respectively. Dropout layers were placed after each dense layer, using the dropout rate determined during the optimization process. The model was initialized with the best weight configuration obtained from earlier optimization trials. Training was performed using the Adam optimizer with the selected learning rate, and the categorical cross-entropy loss function was applied to handle the multi-class classification task. Early stopping was employed to monitor the training process, with training terminated if no improvement in loss was observed for three consecutive epochs. Under these conditions, training concluded at epoch 14 out of the planned 33. The final model achieved an accuracy of 95.34% on the test set, along with a precision of 0.96, recall of 0.94, and an F1-score of 0.95. These results demonstrate that the optimized EfficientNetB1 architecture delivered highly effective performance for solid waste classification.

Evaluation metrics

The performance of machine learning and deep learning models is objectively and statistically evaluated using evaluation measures. Metrics like accuracy, F1-score, precision, recall, and the ROC curve were used in this study to assess how well the solid waste categorization models performed. Performance disparities between the training and test datasets were investigated during the evaluation stage (Yasin and Koklu 2024; Sulak and Koklu 2024). The model's ability to generalize is of paramount importance in this analysis. However, if a model performs well on the training set but significantly worse on the test set, it may indicate overfitting (Koklu and Sulak 2024). The metrics including precision, recall, F1-score, and accuracy (as presented in Fig. 2) were calculated using the weighted average method. This approach accounts for the number of samples in each class, providing a more accurate representation of the model's overall performance, particularly in the presence of imbalanced datasets.

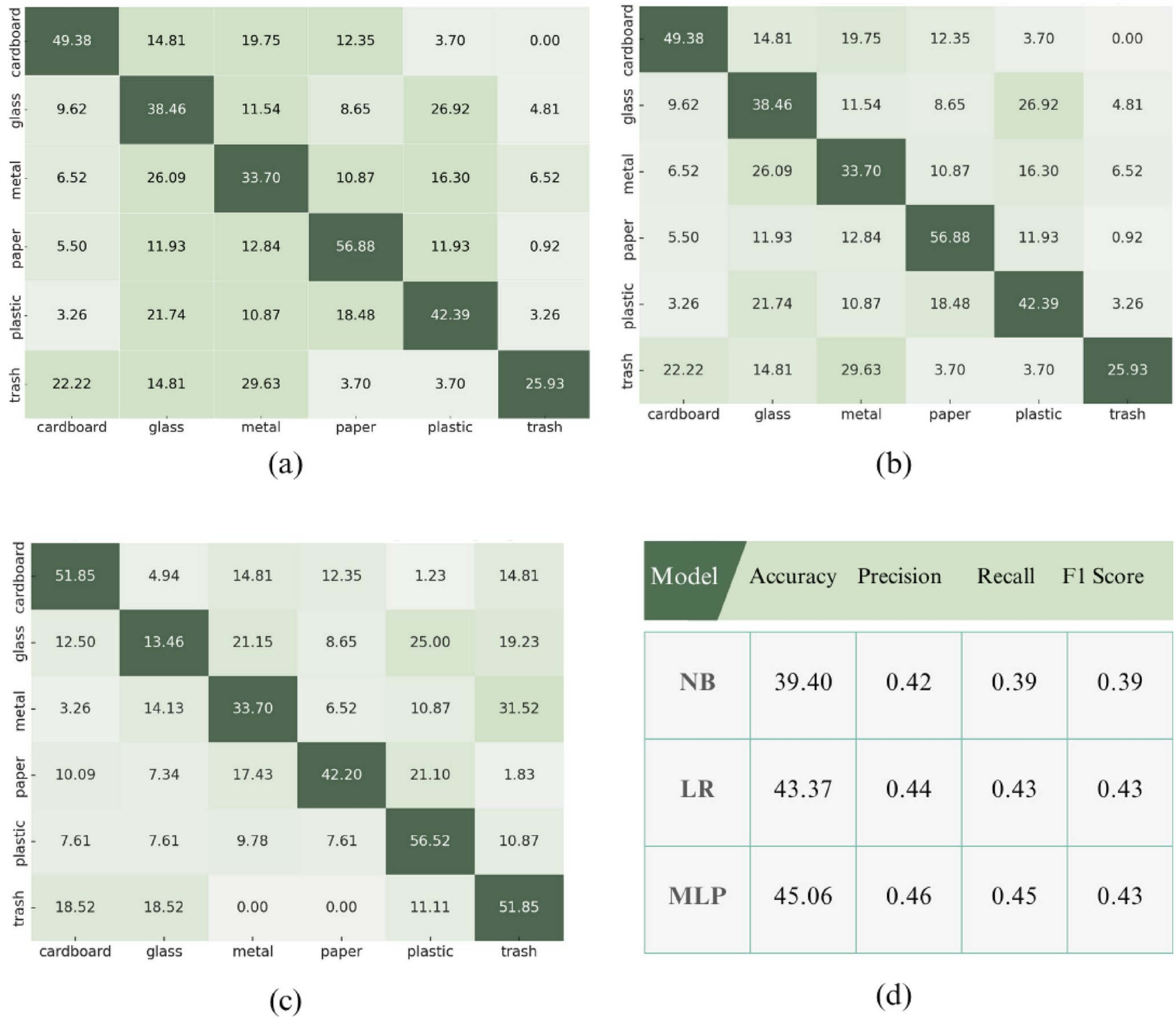
METRIC	FORMULA	DESCRIPTION
PRECISION$_K$	$\frac{TP_k}{TP_k+FP_k}$	The proportion of positive identifications that are actually correct.
WEIGHTED AVERAGE PRECISION	$\sum_{k=1}^{m}(Precision_k\ X\ \frac{N_k}{N_{total}})$	
RECALL$_K$	$\frac{TP_k}{TP_k+FN_k}$	The proportion of actual positives that are correctly identified.
WEIGHTED AVERAGE RECALL	$\sum_{k=1}^{m}(Recall_k\ X\ \frac{N_k}{N_{total}})$	

METRIC	FORMULA	DESCRIPTION
F1 SCORE$_K$	$2\ \text{x} \frac{Precision_k\ x\ Recall_k}{Precision_k + Recall_k}$	The harmonic mean of Precision and Recall.
WEIGHTED AVERAGE F1 SCORE	$\sum_{k=1}^{m}(F1_k\ X\ \frac{N_k}{N_{total}})$	
ACCURACY	$\frac{TP+TN}{TP+TN+FP+FN}$	The proportion of total predictions that are correct.

N_k = number of true instances for class k, m=number of class

$$N_{total} = \sum_{k=1}^{m} N_k$$

Fig. 2 Formulas and definitions of Precision, Recall, F1 Score, and Accuracy metrics



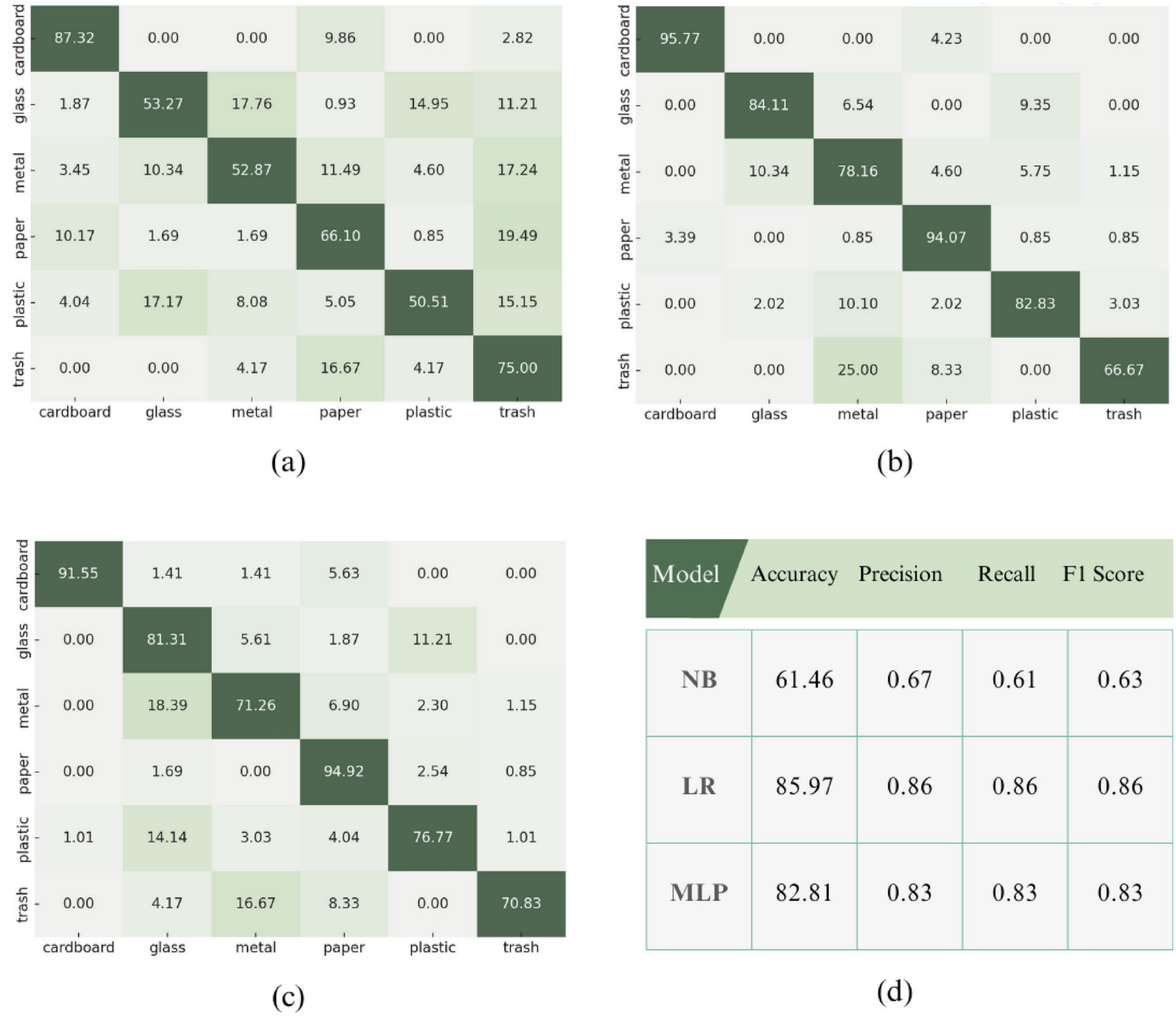
Model	Accuracy	Precision	Recall	F1 Score
NB	39.40	0.42	0.39	0.39
LR	43.37	0.44	0.43	0.43
MLP	45.06	0.46	0.45	0.43

Fig. 3 On the TrashNet dataset, classification outcomes and performance assessments were conducted using Naive Bayes, Logistic Regression, and MLP models. The Naive Bayes model's confusion matrix is displayed in **a**. The Logistic Regression model's confusion matrix is shown in **b**. The MLP model's confusion matrix is shown in **c**. The evaluation metrics for each of the three models are shown in **d**

Results and discussion

Machine learning

Several machine learning algorithms, such as Naive Bayes, Logistic Regression, and MLP, were used in this study to classify solid waste. With an accuracy of 40.18% on the training set and 39.40% on the test set, Naive Bayes performed poorly, according to the models' performance evaluations. This outcome demonstrates its limited ability to capture feature dependencies and its incapacity to classify solid waste efficiently. On the other hand, the Logistic Regression model's accuracy dropped significantly to 43.37% on the test set after reaching 72.93% on the training set. Similarly, on the test set, the MLP model's accuracy was 45.06%, and on the training set, it was 73.48%. Both models' significant performance differences between training and test results point to overfitting and poor generalization ability. Although the MLP had the highest test accuracy of all the machine learning algorithms tested, the discernible performance drop suggests that the model may have learned training data-specific patterns instead of generalizable features. Three hidden layers and one output layer made up the architecture of the top-performing



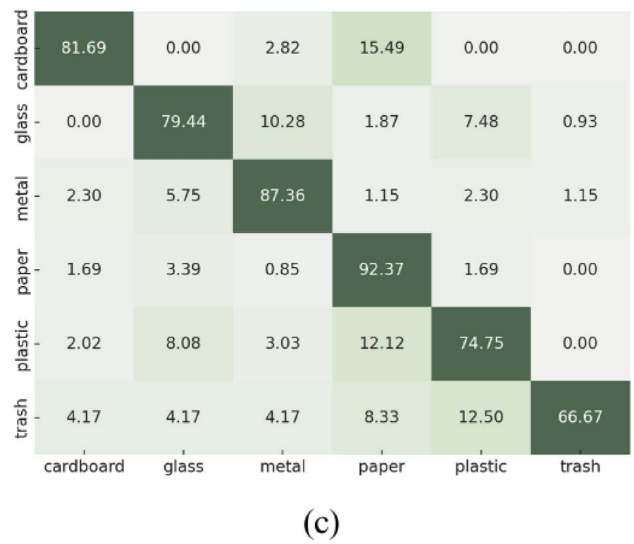
Model	Accuracy	Precision	Recall	F1 Score
NB	61.46	0.67	0.61	0.63
LR	85.97	0.86	0.86	0.86
MLP	82.81	0.83	0.83	0.83

Fig. 4 Classification results and performance evaluations on the TrashNet dataset using features extracted with EfficientNet and machine learning models. **a** shows the confusion matrix for the Naive Bayes model. **b** illustrates the confusion matrix for the Logistic Regression model. **c** presents the confusion matrix for the MLP model. **d** displays the evaluation metrics for all three models

MLP model. There were 64 neurons in each of the first two hidden layers and 32 neurons in the third hidden layer. The output layer, which represented six classes, employed the softmax activation function, while the hidden layers used the ReLU activation function. The categorical cross-entropy loss function was used to train the model, and the Adam method was used to optimize it. This design shows that the MLP model was able to capture more intricate feature correlations in solid waste categorization and generalize more effectively than the other conventional models. The precision attained, however, suggests that more improvement is necessary. The training and test results obtained using the machine learning methods are illustrated in Fig. 3.

Machine learning after feature extraction with deep learning

Features extracted using deep learning models for solid waste classification were evaluated through various machine learning algorithms. Feature vectors were obtained from the deep learning models EfficientNet, MobileNet, and VGG, yielding 15,680, 1,024, and 4,096 features, respectively.



Model	Accuracy	Precision	Recall	F1 Score
NB	63.04	0.65	0.63	0.63
LR	79.45	0.80	0.79	0.79
MLP	82.61	0.83	0.83	0.82

(d)

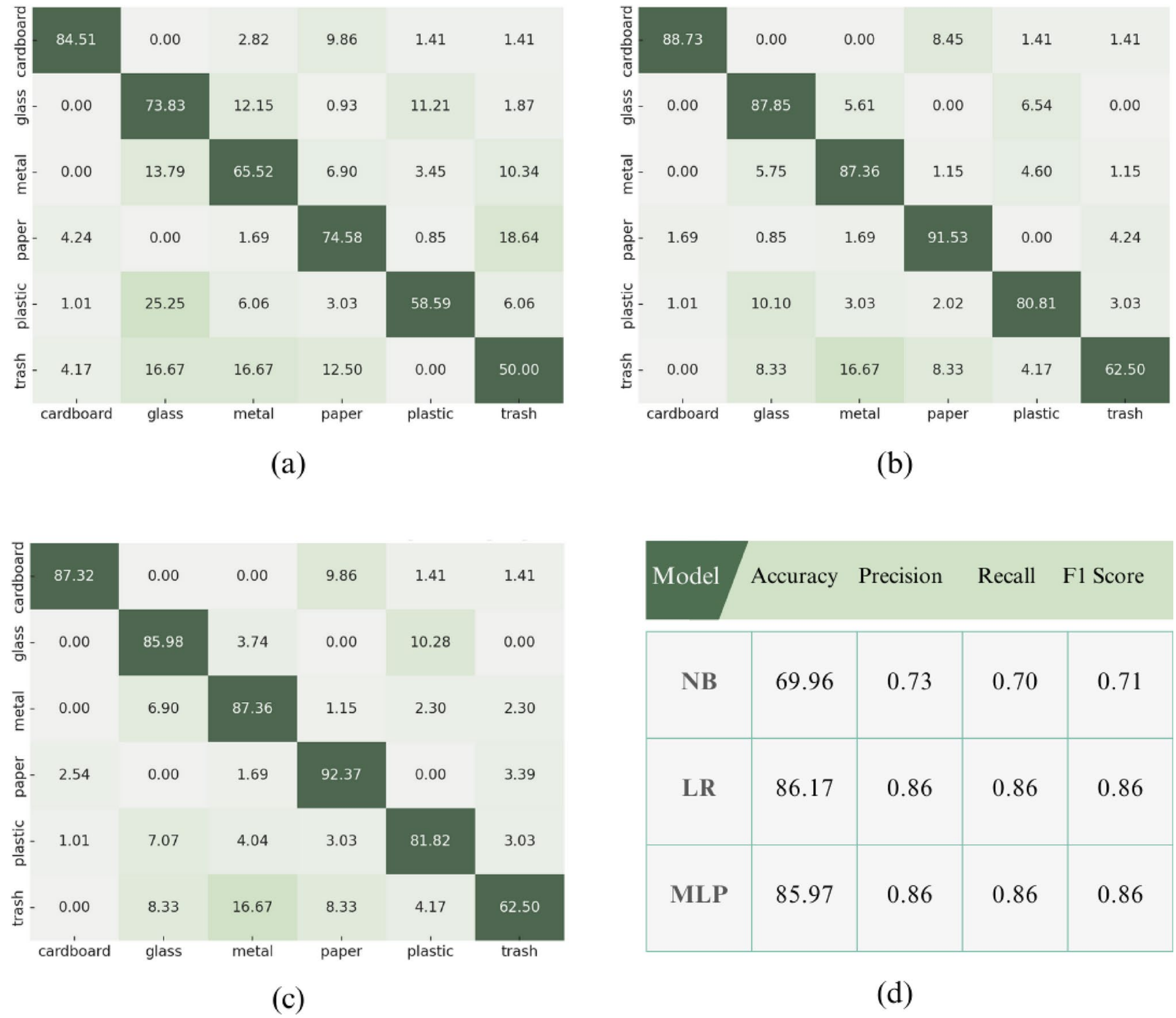
Fig. 5 Classification results and performance evaluations on the TrashNet dataset using features extracted with MobileNet and machine learning models. **a** shows the confusion matrix for the Naive Bayes model. **b** illustrates the confusion matrix for the Logistic Regression model. **c** presents the confusion matrix for the MLP model. **d** displays the evaluation metrics for all three models

These extracted features were then tested using Naive Bayes, Logistic Regression, and MLP algorithms.

In experiments conducted on features extracted from EfficientNet, the Naive Bayes algorithm achieved an accuracy of 61.46%, Logistic Regression achieved 85.97%, and MLP achieved 82.81%. These results indicate that the Logistic Regression algorithm was able to utilize the extracted features most effectively for classification. Figure 4 presents the confusion matrices and evaluation metrics corresponding to the machine learning models.

Using the features extracted with the MobileNet model, the Naive Bayes algorithm achieved an accuracy of 63.04%, Logistic Regression achieved 79.45%, and MLP achieved 82.61%. The test results are presented in Fig. 5. These findings demonstrate that the MLP algorithm effectively utilized the features extracted by the MobileNet model for solid waste classification.

Finally, in the classifications performed using features extracted with the VGG model, the Naive Bayes algorithm achieved an accuracy of 69.96%, Logistic Regression achieved 86.17%, and MLP achieved 85.97%. As shown in Fig. 6, Logistic Regression obtained the highest accuracy in this test group, demonstrating superior performance



Model	Accuracy	Precision	Recall	F1 Score
NB	69.96	0.73	0.70	0.71
LR	86.17	0.86	0.86	0.86
MLP	85.97	0.86	0.86	0.86

Fig. 6 Classification results and performance evaluations on the TrashNet dataset using features extracted with VGG and machine learning models. a shows the confusion matrix for the Naive Bayes model. b illustrates the confusion matrix for the Logistic Regression model. c presents the confusion matrix for the MLP model. d displays the evaluation metrics for all three models

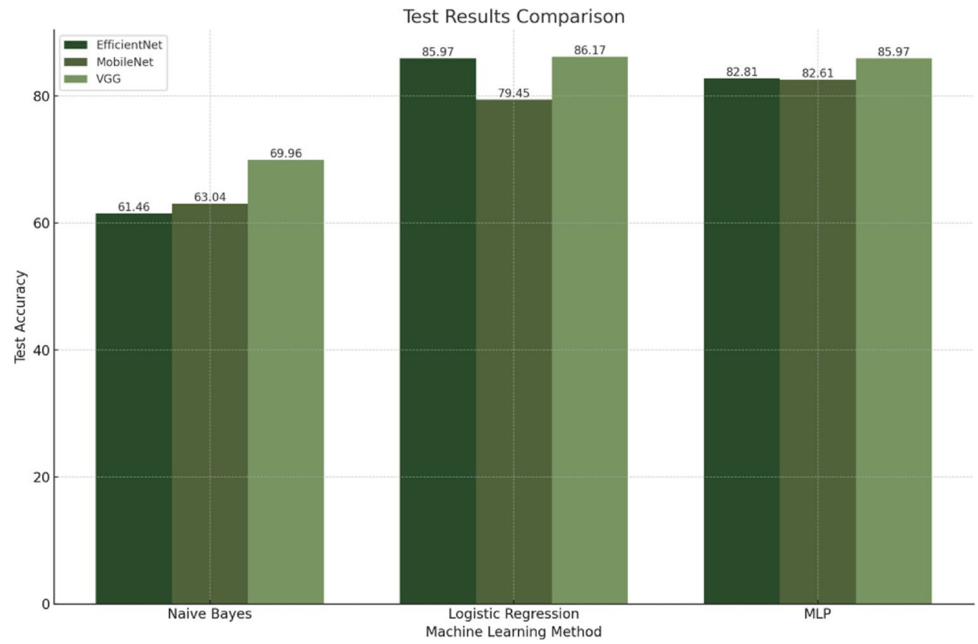
compared to the other models, particularly in classifying features extracted by the VGG model.

The findings of this study demonstrate that features extracted by different deep learning models can be effectively classified using various machine learning algorithms. Overall, the Logistic Regression algorithm achieved the highest performance across different feature sets, exhibiting better generalization capability and a stronger ability to learn complex relationships between features compared to the other models in solid waste classification. These results highlight the advantages of integrating deep learning and machine learning approaches for solid waste management applications. Figure 7 and the subsequent figures present the test accuracy percentages of the EfficientNet, MobileNet, and VGG feature sets when applied to the Naive Bayes, Logistic Regression, and MLP models.

Model selection for hyperparameter optimization

Among the evaluated deep learning models (EfficientNet, MobileNet, and VGG), EfficientNet was selected for hyperparameter optimization with GWO due to its architectural efficiency and practical suitability for optimization.

Fig. 7 Test accuracies achieved using Naive Bayes, Logistic Regression and MLP models with features extracted from EfficientNet, MobileNet, and VGG



Although VGG16 achieved slightly higher accuracy than EfficientNet in some feature extraction-based classification tasks, it contains approximately 138 million parameters, compared to 7.8 million in EfficientNetB1. This substantial difference results in a significantly higher computational load and longer training time for VGG16. In contrast, EfficientNet provides a better trade-off between model size and performance, making it more feasible for further optimization and potential real-world deployment. Therefore, EfficientNetB1 was chosen as the base model for end-to-end training and hyperparameter tuning, while the other models were used exclusively for feature extraction.

EfficientNet hyperparameter optimization with GWO

Hyperparameter optimization was carried out using the EfficientNetB1 architecture, selected for its balance between accuracy and computational efficiency. To take advantage of transfer learning, pretrained weights from the ImageNet dataset were used to initialize the model. Thirty distinct hyperparameter configurations were first assessed, each of which was trained on the training data for one epoch. As the baseline initialization, the configuration with the highest validation accuracy was chosen, and the weights associated with it were kept. The GWO, which methodically investigated the hyperparameter space to fine-tune parameters like the learning rate, dropout rate, and number of dense layers in the classification head, was then started using these weights and architectural settings. Only the classification head of EfficientNetB1 was optimized during this process; the convolutional backbone remained frozen.

The hyperparameters targeted during optimization included the learning rate, dropout rate, and number of dense layers. The ranges for these parameters were set as follows:

- Learning rate: 0.0001 to 0.01
- Dropout rate: 0.00001 to 0.999999
- Number of dense layers: 0 to 3

The model's test accuracy was used to determine the ideal parameters at the conclusion of each iteration. This method made it possible to determine the ideal set of hyperparameters to improve the model's overall performance. By monitoring the highest accuracy scores attained throughout iterations, the robustness of the optimization process was assessed, offering important insight into how these modifications enhanced the model's classification performance. This stage is thought to be essential for allowing deep learning models to perform better when working with difficult datasets. Figure 8 shows the workflow for the hyperparameter optimization process and demonstrates how the CNN model and GWO algorithm are integrated.

Although the GWO significantly improved the classification performance of the EfficientNetB1 model, it introduced additional computational overhead. In this study, GWO was executed for 100 iterations, with each iteration

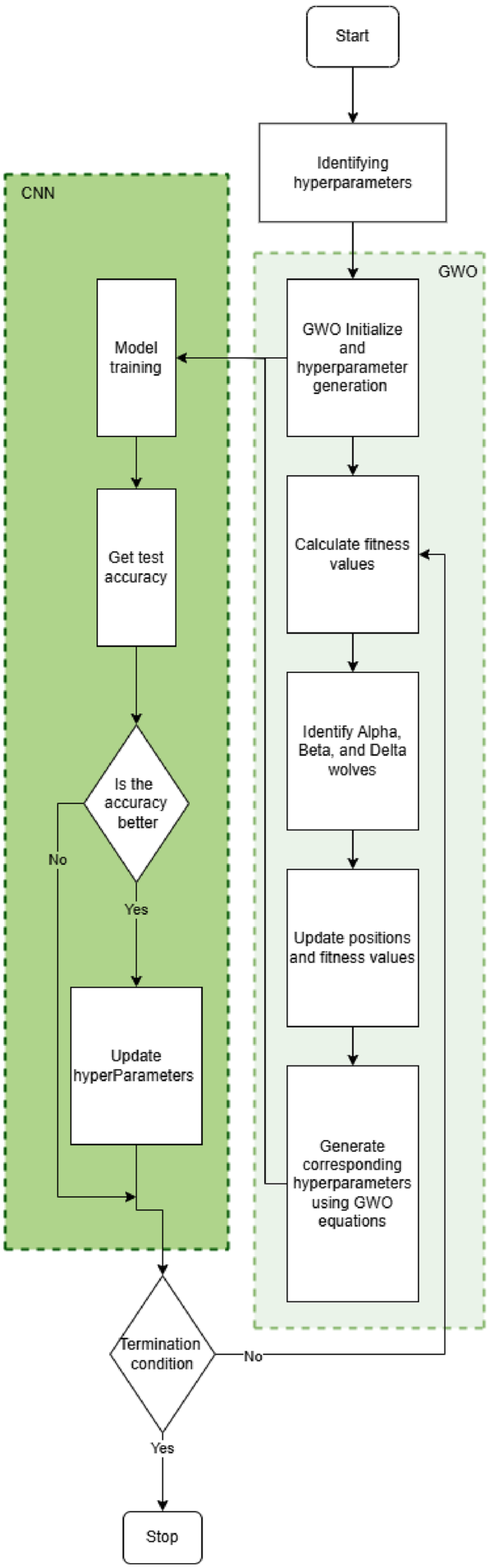


Fig. 8 Flow Diagram for Hyperparameter Optimization of CNN Using GWO

evaluating a candidate hyperparameter configuration for one epoch to identify promising parameter sets. While this process increased training time during the development phase, it was performed offline and only once. Therefore, it did not affect the inference time or deployment efficiency of the final model. Future studies may explore alternative optimization techniques with lower computational requirements, such as Bayesian Optimization or early-stopping-based search strategies.

- Fig. 9 presents the convergence curve, illustrating the variation in the best score of the GWO algorithm across iterations.
- Precision, recall, and F1-score metrics for each waste class after hyperparameter optimization are shown in Table 1. These class-wise performance metrics provide important information about how well the model can differentiate between various waste kinds. The findings show that the model performed well in both identifying and accurately classifying waste types, with good recall and precision across the majority of classes.
- Fig. 10 visualizes the model's performance in terms of correct and incorrect classifications for different waste classes after hyperparameter optimization.
- Fig. 11 displays the Receiver Operating Characteristic (ROC) curves for each waste class, highlighting the model's discriminative capability and overall classification effectiveness.

The study examined the effects of features extracted using different deep learning models on Naive Bayes, Logistic Regression, and MLP classifiers. As shown in Table 2, features extracted with deep learning models such as EfficientNet, MobileNet, and VGG significantly improved classification accuracy. Additionally, the EfficientNet model optimized with GWO achieved the highest accuracy.

Conclusion

This study evaluated the effectiveness of deep learning and machine learning methods for solid waste classification. Among the machine learning approaches, Naive Bayes, Logistic Regression, and MLP exhibited relatively low performance. Features extracted by deep learning models (EfficientNet, MobileNet, and VGG) were classified using Naive Bayes, Logistic Regression, and MLP classifiers. In addition, model hyperparameter optimization strategies were implemented. The GWO was applied to optimize the hyperparameters of the EfficientNet model, achieving a high classification accuracy of 95.43%. Training was conducted using the parameters that provided the best performance after

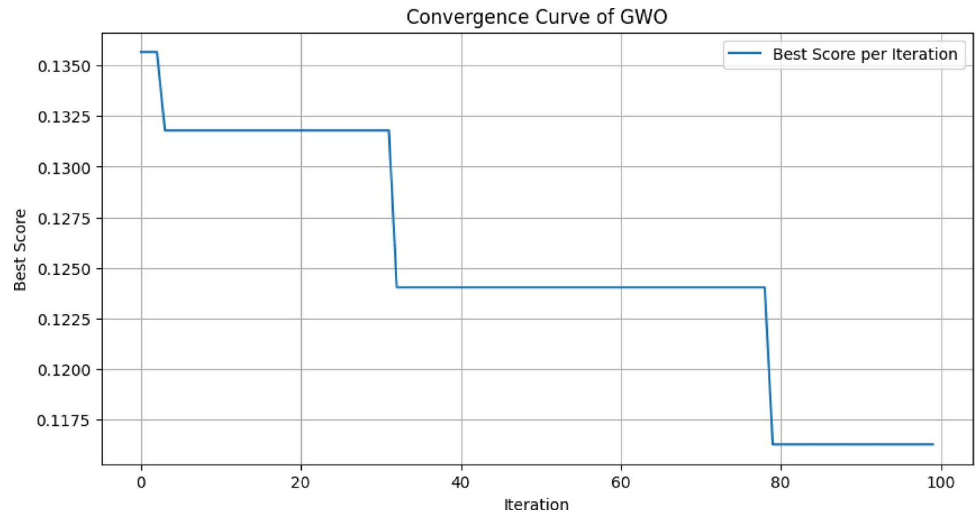


Fig. 9 The convergence curve of GWO. The change in the best score across iterations is shown

Table 1 Precision, recall, and F1-score values for each waste class after hyperparameter optimization

Class	Precision	Recall	F1-Score
Cardboard	1	0,98	0,99
Glass	0,92	0,94	0,93
Metal	0,95	0,98	0,96
Paper	0,94	1	0,97
Plastic	0,96	0,92	0,94
Trash	1	0,8	0,89

Fig. 10 The confusion matrix of test results after hyperparameter optimization

optimization, and an early stopping criterion was applied after 14 epochs. This strategy enhanced training efficiency while preventing potential overfitting. The results confirm the strong performance of deep learning models in accurately classifying solid waste.

This study also looked at the applicability of deep learning and machine learning approaches in the context of environmental sustainability and the possibility of combining them for solid waste classification. Classification performance was successfully enhanced by combining machine learning algorithms with features that were extracted using deep learning models. Nevertheless, the deep learning strategy improved by hyperparameter optimization demonstrated its superiority over conventional techniques by achieving noticeably higher accuracy and robustness.

With only 2,527 labeled images, the TrashNet dataset is comparatively small and has limited diversity, which is one of the study's main limitations. It does not accurately capture the variability seen in actual waste conditions, such as variations in lighting, object deformation, occlusion, and cleanliness, even though it offers a consistent standard for preliminary testing. This constraint could result in biased learning and limit the model's capacity to generalize efficiently across various waste scenarios. Future research should use bigger and more diverse datasets gathered from various sources and environmental contexts to address this problem. By adding these datasets, deep learning models' generalization and robustness would be improved, increasing their suitability for solid waste classification systems in the real world. The lack of field testing in real-world settings is another significant limitation of this study. Even though the

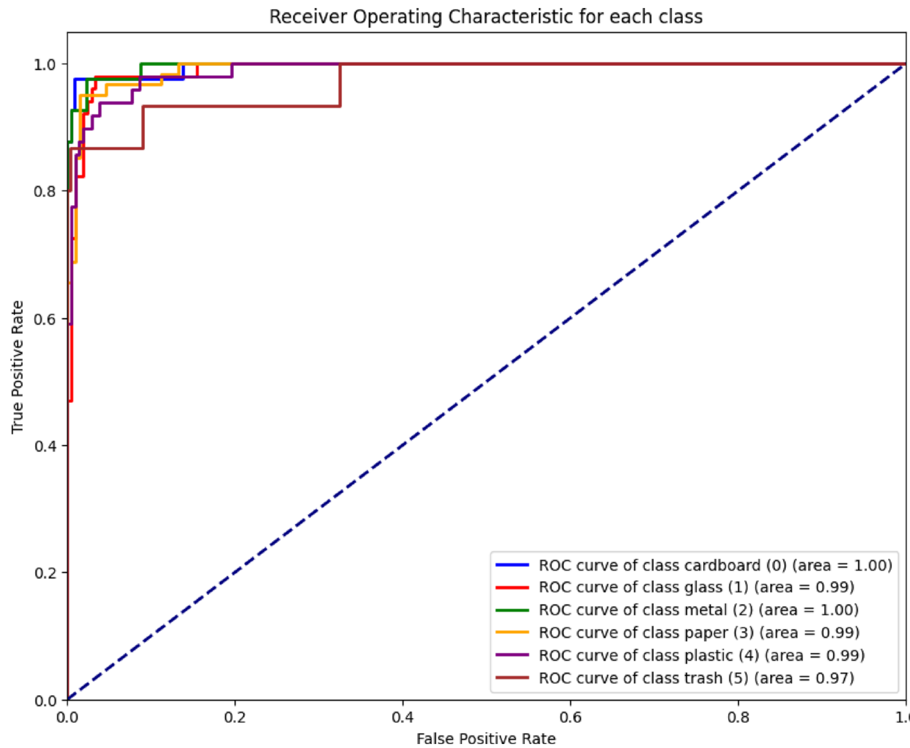


Fig. 11 ROC curves for each class

Table 2 Accuracy Rates of Different Feature Extraction Methods and Classification Algorithms

Feature extraction method	Classification method	Accuracy (%)
-	Naive bayes	39.4
-	Logistic regression	43.37
-	MLP	45.06
EfficientNet	Naive bayes	61.46
EfficientNet	Logistic regression	85.97
EfficientNet	MLP	82.81
MobileNet	Naive bayes	63.04
MobileNet	Logistic regression	79.45
MobileNet	MLP	82.61
VGG	Naive bayes	69.96
VGG	Logistic regression	86.17
VGG	MLP	85.97
-	**EfficientNet with GWO optimization**	**95.43**

Bold indicate that the highest accuracy rate has been achieved

model performed well on a static, carefully selected dataset, real-world deployment scenarios frequently involve intricate elements like fluctuating lighting, partial occlusions, overlapping trash, and contamination (such as soiled or warped objects). These elements have a significant impact on classification performance. The model's deployment in working waste sorting systems and thorough field tests to gauge its resilience, adaptability, and practical usability should be the top priorities of future research. Such testing will be crucial for confirming the efficacy of the model as well as for spotting any potential flaws that static datasets might overlook. The possibility of cultural bias in waste classification tasks is another crucial but frequently disregarded factor. Regions and cultures can differ greatly in terms of waste composition, sorting techniques, and what constitutes recyclable material. For example, variations in local recycling laws, food packaging, and consumption patterns affect the type and appearance of waste products. The model may have learned region-specific characteristics because the dataset used in this study (TrashNet) comes from a particular geographical and cultural context. This could limit the model's performance in environments with different cultural norms. Therefore, datasets gathered from various geographic locations should be included in future studies in order to reduce these biases and create classification schemes that are more broadly applicable. Additionally, assessing the model's performance in test scenarios with varying cultural backgrounds will help guarantee equity and inclusivity in practical applications. To confirm the generalizability and superiority of the GWO-based approach, future research should also compare it to other optimization techniques like Bayesian Optimization and Genetic Algorithms, as well as other deep learning architectures like ResNet or DenseNet. While early stopping was successful in avoiding overfitting during training, future research should look into additional methods like data augmentation and regularization to improve the model's capacity for generalization and noise tolerance.

Although this study does not include a direct quantification of energy savings or carbon footprint reduction, it is well established in the literature that accurate waste sorting significantly reduces the energy required for recycling processes compared to raw material extraction. By improving classification accuracy through model optimization, the proposed method contributes indirectly to sustainability by lowering the energy intensity and carbon emissions associated with misclassification and manual sorting efforts. Future research will focus on estimating energy and emission reductions based on classification accuracy improvements using life cycle assessment (LCA) frameworks.

The findings suggest that expanding the variety and scope of the datasets can improve the model's capacity for generalization. The model should be able to generalize more effectively across various waste types and environmental conditions if it is trained using larger and more diverse datasets from various sources. Additionally, the model can be integrated into practical waste management systems to improve operational efficiency and minimize environmental footprints. Field testing of the model is highly important to assess its practical applicability and to identify potential limitations that may not emerge in controlled experimental conditions. Conclusions Deep learning and machine learning techniques, when specifically applied to solid waste classification, hold great potential to enhance the efficiency and environmental responsibility of waste management systems. The integration of these technologies is expected to form a foundation for future policies and practices that promote environmental sustainability. This study contributes to the growing body of research in this field and opens new directions for developing intelligent, data-driven, and sustainable waste management solutions.

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Data availability Accessing the study's dataset can be found here: https://github.com/garythung/trashnet

Declarations

Conflict of interest The authors declare no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors. This study does not involve any ethical concerns or require ethical approval.

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