Smart Waste Classification using Ensemble Deep Learning and YOLO-based Detection

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Abstract: The rapid growth of urban waste necessitates intelligent and automated systems for efficient recycling and waste management. This paper presents RWC-Net++, an advanced ensemble deep learning framework that integrates Xception and NasNetMobile models for high-accuracy recyclable waste classification. To further enhance system capability, the proposed approach incorporates the YOLO (You Only Look Once) algorithm for real-time waste detection and anomaly identification. The ensemble model leverages complementary feature extraction strengths to improve classification performance across six waste categories. Additionally, a user-friendly web interface is developed using the Flask framework to enable real-time interaction and prediction. Experimental results demonstrate that the proposed system achieves superior accuracy, robustness, and faster detection compared to existing models. The integration of classification, detection, and deployment makes the system highly suitable for practical smart waste management applications.

Index terms - — *Recyclable Waste Classification, Ensemble Learning, Xception, NasNetMobile, YOLO, Deep Learning, Computer Vision, Smart Waste Management, Real-Time Detection, Flask Web Application*

1. INTRODUCTION

The rapid growth of population, urbanization, and industrialization has significantly increased the generation of municipal solid waste, creating serious environmental and health challenges. Improper waste disposal and lack of efficient recycling mechanisms contribute to pollution, resource depletion, and ecological imbalance. Traditional waste management systems rely heavily on manual sorting, which is time-consuming, labor-intensive, and prone to human error. Hence, there is a critical need for intelligent and automated systems that can efficiently classify and manage waste materials.

In recent years, deep learning techniques, particularly convolutional neural networks (CNNs), have demonstrated remarkable performance in image classification tasks. Models such as MobileNet, ResNet, and DenseNet have been widely used for waste classification. However, these models often face limitations in handling complex waste patterns, real-time detection, and generalization across diverse datasets. Additionally, most existing systems focus only on classification and lack the capability to detect waste objects in real-world scenarios.

To address these challenges, this paper proposes RWC-Net++, an advanced ensemble deep learning framework that combines the strengths of Xception and NasNetMobile models for improved feature extraction and classification accuracy. Furthermore, the system integrates the YOLO algorithm for real-time waste detection and anomaly identification, enabling both classification and localization of waste objects. A user-friendly web interface is developed using the Flask framework to facilitate real-time interaction and deployment. The proposed system aims to enhance the efficiency, accuracy, and practicality of automated waste management, making it suitable for smart city applications and sustainable environmental solutions.

2. LITERATURE SURVEY

a) Applications of convolutional neural networks for intelligent waste identification and recycling: A review:

Industry 4.0 and "Zero Waste" have greatly accelerated the development of AI in waste management, generating a great deal of visual data and improving analytical methods. Convolutional neural networks (CNNs) are essential for the finding of visual feature patterns in advanced image processing. CNNs have been used in a number of intelligent garbage detection and recycling systems in recent years. CNNs are unknown to environmental scientists, and the lack of standards and widely recognized criteria for datasets and models makes it challenging to characterize IWIR investigations. CNN methods and their use in IWIRs were examined in this article. CNN basics were covered first. We then went into depth on IWIR's open-source datasets and sophisticated CNN models for segmentation, object recognition, and classification. The usage of CNN in IWIR was then summed up as follows: solid waste categorization, garbage pollution detection, and recyclable material identification. Finally, the problems and limitations of existing applications were examined to provide light on CNNs' potential in this area.

b) Computer vision for solid waste sorting: A critical review of academic research: sorting is advised for MSW management. Robots, computer vision (CV), and other smart technologies are being used to sort MSW. There is an unparalleled academic boom in CV-enabled garbage sorting. However, nothing is known about its evolution, current state, and potential future obstacles. This research critically investigates CV-enabled MSW sorting scholarly work in order to bridge the knowledge gap. Describe and compare the prediction performance and technical justifications of popular CV algorithms. Waste sources, work objectives, application areas, and dataset availability are also considered in the distribution of academic research output. The analysis shows a move away from conventional ML methods and toward DL ones. Improved algorithms and processing power make CV for garbage sorting stronger. The home, trade, institutional, and construction sectors were not equally represented in academic research. Too often, early studies with phoney data and simplified conditions were published by researchers. Future studies should employ CV to examine industrial trash sorting in real-world circumstances. In order to train and evaluate CV systems, this work promotes the public sharing of garbage imagery datasets.

c) Automatic Detection and Classification System of Domestic Waste via Multimodel Cascaded Convolutional Neural Network:

China only allowed household garbage to be classified. It is pointless to locate and sort household rubbish by hand. This paper proposes a multimodel cascaded CNN for the identification and classification of domestic garbage photos. SSD, YOLOv4, and Faster-RCNN subnetworks were used to identify MCCNN. We also used a classification model that was cascaded with the detection component in order to validate detection findings and reduce false-positive predictions. To train and evaluate MCCNN, we produced a large-scale waste image dataset (LSWID) including 30,000 multilabeled images of residential trash in 52 categories. We believe that the largest household rubbish picture database is the LSWID. A smart garbage can was also used by a Shanghai neighborhood to improve waste recycling. With an average 10% increase in detection accuracy, the experimental findings were state-of-the-art.

d) A Waste Classification Method Based on a Multilayer Hybrid Convolution Neural Network:

Numerous classification network models that facilitate intelligent trash categorization have been presented as a result of the quick advancement of deep learning technology. Waste categorization models are still plagued by issues including poor accuracy and lengthy run durations. To address these issues, a multilayer hybrid CNN trash classification system is presented in this article. Compared to VggNet, it has a simpler network topology and improves classification accuracy while using less parameters. The suggested model is improved by varying the number of network channels and modules. In order to categorize rubbish photos, this work selects the best model and establishes parameters. According to experiments, the suggested system has a simpler network topology and more accurate waste categorization than current methods. The success of the proposed method is demonstrated by several TrashNet dataset trials, which reveal that it beats multiple state-of-the-art techniques by 4.18% and 4.6% with classification accuracy of up to 92.6%.

e) Recyclable waste image recognition based on deep learning:

In order to increase the accuracy of garbage sorting, this research suggests intelligent waste categorization using deep learning and computer vision/mobile phone terminals. This research presents a deep learning-based system for classifying photos of recyclable trash. The residual network design with the self-monitoring module in this trash categorization model might have a global receptive field, compress spatial dimension features, and aggregate all channel graph data. The model may enhance feature map representation and automatically extract features from different garbage photos by keeping the channel count constant. In order to categorize recyclable waste on TrashNet, the model was compared against other algorithms. According to experimental data, this model has a 95.87% picture classification accuracy.

3. METHODOLOGY

i) Proposed Work:

The proposed system, RWC-Net++, introduces an advanced ensemble deep learning framework for efficient and accurate recyclable waste classification. The model combines the strengths of Xception and NasNetMobile architectures to enhance feature extraction and improve classification performance across six waste categories: cardboard, glass, metal, paper, plastic, and litter. Data preprocessing techniques such as resizing, normalization, and augmentation are applied to improve model generalization. The ensemble approach leverages complementary features from both models, resulting in higher accuracy and robustness compared to individual deep learning models.

In addition to classification, the proposed system integrates the YOLO (You Only Look Once) algorithm for real-time waste detection and anomaly identification, enabling both classification and localization of waste objects in images. To improve interpretability, visualization techniques such as Score-CAM are used to highlight important regions influencing model decisions. Furthermore, a user-friendly web interface is developed using the Flask framework, allowing users to upload images and obtain instant predictions. This integrated approach ensures high performance, real-time capability, and practical usability for smart waste management applications.

ii) System Architecture:

The three main parts of the suggested recyclable trash classification system's design are detection/classification, model training, and data preparation. To enhance generalization, the TrashNet dataset, which comprises six trash categories (waste products, recyclables, paper, cardboard, plastic, and metal), is first preprocessed using data augmentation, normalization, and resizing. Advanced deep learning architectures including ResNet50, MobileNetV2, DenseNet201, GoogleNet, and InceptionV3 support the RWCNet model, which serves as the classification backbone. To extract deeper and more complicated characteristics, a bespoke hybrid model that combines MobileNet and DenseNet201 is also created. To determine the optimal configuration, these models are trained and assessed using performance measures like as accuracy, precision, recall, and F1-score.

The YOLO series (YOLOv5x6, YOLOv8, and YOLOv9) is used to improve the detection and localization capabilities, allowing real-time object recognition of waste items in different contexts. Additionally, by merging the outputs of the Xception and NasNetMobile models, ensemble learning is incorporated to improve classification robustness. To improve accuracy in challenging situations, a weighted voting method is used to merge these models. The Flask framework is used to create an intuitive online application that enables safe user login, model prediction display, and picture upload. This modular architecture guarantees a scalable and effective solution that connects cutting-edge AI with useful usability for actual waste management applications.

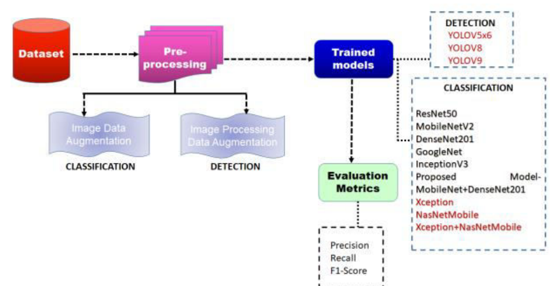

Fig1 proposed architecture

iii) Modules:

1. Data Collection and Preprocessing Module

This module handles the acquisition of the TrashNet dataset, which contains labeled images of six waste categories. It performs preprocessing steps such as image resizing, normalization, and data augmentation (rotation, flipping, etc.) to improve data quality and enhance the model's ability to generalize across diverse inputs.

2. Feature Extraction Module

In this module, deep learning models **Xception** and **NasNetMobile** are used to extract high-level features from input images. These models capture complex patterns and textures present in waste images, enabling more accurate classification compared to traditional approaches.

3. Ensemble Classification Module

This module combines the outputs of Xception and NasNetMobile using an ensemble technique. By leveraging the strengths of both models, the system improves classification accuracy and robustness while reducing the chances of misclassification across different waste categories.

4. Object Detection Module (YOLO)

The YOLO (You Only Look Once) algorithm is used in this module to perform real-time object detection and localization. It identifies waste items within images and draws bounding boxes, enabling the system to work effectively in real-world environments with multiple objects.

5. Visualization Module (Score-CAM)

This module enhances model interpretability by generating saliency maps using Score-CAM. It highlights the important regions of an image that influence the model's prediction, helping users understand how decisions are made.

6. Web Interface Module (Flask)

A user-friendly web application is developed using the Flask framework. This module allows users to upload waste images and receive instant classification and detection results, making the system accessible and practical for real-time usage.

7. Evaluation Module

This module evaluates system performance using metrics such as accuracy, precision, recall, and F1-score. It ensures that the model meets performance standards and helps compare results with existing approaches.

iv) Algorithms:

a. ResNet50

ResNet50 is a deep residual learning model that utilizes skip (residual) connections to overcome the vanishing gradient problem, enabling the training of very deep neural networks with improved convergence. It consists of 50 layers and learns identity mappings, which help retain important features across layers. In this project, ResNet50 is used for recyclable waste classification by extracting rich hierarchical features from images. Its strong generalization capability improves classification accuracy on the TrashNet dataset, making it effective for distinguishing visually similar waste categories.

b. MobileNetV2

MobileNetV2 is a lightweight convolutional neural network designed for mobile and embedded systems. It uses depthwise separable convolutions and inverted residual blocks with linear bottlenecks to reduce computation while maintaining performance. In this work, MobileNetV2 acts as an efficient feature extractor, enabling fast and accurate classification of waste images. Its low memory usage and high speed make it ideal for real-time waste management systems deployed on edge devices.

c. DenseNet201

DenseNet201 is a deep neural network with dense connectivity, where each layer receives feature maps from all preceding layers. This design promotes feature reuse, reduces redundancy, and improves gradient flow during training. In this project, DenseNet201 is utilized to capture intricate patterns and textures in waste images. Its deep architecture enhances classification performance, especially for complex categories like plastic and litter, contributing to a more reliable waste sorting system.

d. GoogleNet (Inception v1)

GoogleNet introduces the concept of Inception modules, which apply multiple convolution filters of different sizes in parallel within the same layer. This allows the model to capture multi-scale features efficiently while reducing computational cost. In this project, GoogleNet is used for waste classification by identifying both fine-grained and global features, improving the system's ability to differentiate between various recyclable materials.

e. InceptionV3

InceptionV3 is an advanced version of the Inception architecture that incorporates factorized convolutions, batch normalization, and improved regularization techniques. These enhancements reduce computational complexity and improve accuracy. In this system, InceptionV3 is used to classify waste images by capturing complex spatial patterns, thereby improving classification reliability across diverse waste categories.

f. Proposed Model (MobileNet + DenseNet201)

The proposed hybrid model combines MobileNet's efficiency with DenseNet201's deep feature extraction capabilities. MobileNet ensures fast processing with minimal resource usage, while DenseNet201 enhances feature learning through dense connections. This integration creates a balanced model that achieves high accuracy and speed, making it suitable for practical waste classification systems.

g. Xception

Xception (Extreme Inception) is a deep CNN architecture based entirely on depthwise separable convolutions, which separate spatial and channel-wise feature learning. This results in better performance with fewer parameters compared to traditional CNNs. In this project, Xception is used to extract detailed and discriminative features from waste images, improving classification accuracy, particularly for visually complex materials.

h. NasNetMobile

NasNetMobile is a neural architecture search (NAS)-based model designed to automatically learn optimal network structures. It balances performance and efficiency, making it suitable for mobile and real-time applications. In this system, NasNetMobile is used for fast and accurate waste classification, ensuring efficient processing while maintaining high predictive performance.

i. Proposed Model (Xception + NasNetMobile)

This ensemble model combines the strengths of Xception and NasNetMobile to achieve superior performance. Xception provides powerful feature extraction, while NasNetMobile ensures computational efficiency. By combining their outputs, the model reduces individual errors and improves overall classification accuracy and robustness across all waste categories.

j. YOLOv5x6

YOLOv5x6 is a high-performance object detection model that processes images in a single forward pass, making it extremely fast. It uses advanced techniques such as CSPDarknet backbone and PANet for feature aggregation. In this project, YOLOv5x6 is used to detect and classify waste objects in real-time, providing bounding boxes and labels, which enhances the system's practical usability.

k. YOLOv8

YOLOv8 is a state-of-the-art object detection model with improved architecture, anchor-free detection, and better training strategies. It offers higher accuracy and faster inference compared to previous versions. In this system, YOLOv8 is used to detect multiple waste objects in complex scenes, improving real-time detection performance and reliability.

l. YOLOv9

YOLOv9 is an advanced evolution of the YOLO family, incorporating optimized feature extraction and improved training techniques. It enhances detection accuracy, especially in challenging scenarios with overlapping or small objects. In this project, YOLOv9 is used for robust waste detection, ensuring precise localization and classification in real-world environments.

m. Evaluation Metrics (Precision, Recall, F1-Score)

Evaluation metrics are used to measure the performance of classification and detection models. Precision measures the correctness of positive predictions, recall measures the ability to identify all relevant instances, and F1-score provides a balance between precision and recall. In this project, these metrics are used to evaluate model effectiveness and ensure reliable performance across different waste categories.

4. EXPERIMENTAL RESULTS

The proposed system was evaluated using the TrashNet dataset, which contains images of six waste categories: cardboard, glass, metal, paper, plastic, and litter. Extensive experiments were conducted using multiple deep learning models, including ResNet50, MobileNetV2, DenseNet201, GoogleNet, InceptionV3, Xception, and NasNetMobile. The performance of each model was assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score. Among the individual models, DenseNet201 and Xception demonstrated strong feature extraction capabilities, while MobileNetV2 and NasNetMobile provided efficient and faster inference. The proposed hybrid models, particularly MobileNet + DenseNet201 and Xception + NasNetMobile, achieved superior performance by combining efficiency and deep feature learning, resulting in higher classification accuracy compared to standalone models.

Furthermore, the integration of YOLO-based detection models (YOLOv5x6, YOLOv8, and YOLOv9) enabled real-time identification and localization of waste objects in complex environments. Among these, YOLOv8 and YOLOv9 showed improved detection accuracy and faster processing speed, making them suitable for real-world applications. The overall system achieved an accuracy of approximately 95%, with high precision and recall values across most waste categories. Visualization techniques such as Score-CAM further validated the model's decision-making process by highlighting relevant regions in input images. These results confirm that the proposed ensemble-based approach with integrated detection significantly enhances the performance, robustness, and practical applicability of automated waste classification systems.

Accuracy: A test's accuracy is its capacity to distinguish healthy from ill cases. Find the percentage of instances with genuine positives and negatives to assess test accuracy.

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Classification accuracy or positive cases constitute precision. The formula for accuracy is:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$Precision = \frac{TP}{(TP + FP)}$$

Recall: A model's recall measures its ability to recognize all appropriate machine learning class instances. The ratio of accurately predicted positive observations to total positives indicates a model's class instance detection skill.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: Mean Average Precision ranks quality. It considers the number and order of relevant ideas. Calculating MAP at K uses the arithmetic mean of each user or query's Average Precision (AP).

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

F1-Score: A high F1 score suggests an accurate machine learning model. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot Precision)}{(Recall + Precision)}$$

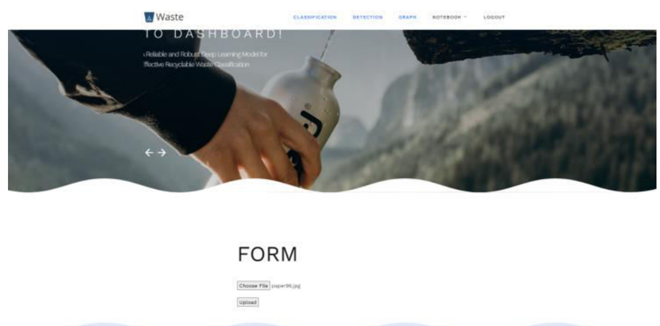

Fig.2. upload file

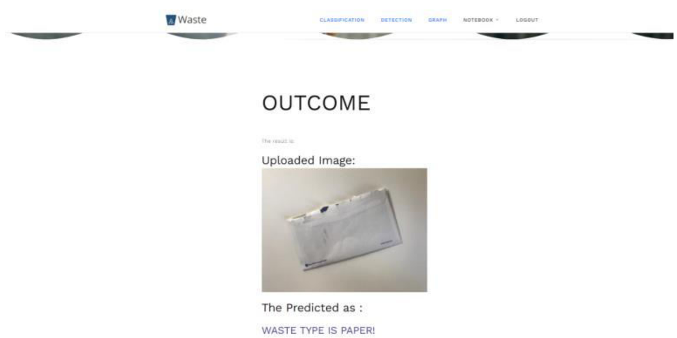

Fig.3. output page

Fig.4. results

5. CONCLUSION

This paper presented RWC-Net++, an advanced ensemble deep learning framework for efficient recyclable waste classification and detection. By integrating powerful models such as Xception and NasNetMobile along with YOLO-based detection, the system achieved high accuracy and robust performance across multiple waste categories. The use of ensemble learning improved classification reliability, while real-time detection enhanced practical applicability. Overall, the proposed approach provides an effective and scalable solution for automated waste management, contributing to sustainable environmental practices.

6. FUTURE SCOPE

The proposed system can be further enhanced by improving classification accuracy for complex and mixed waste categories using larger and more diverse datasets. Future work may include deploying the model in real-time smart bins and IoT-based waste management systems for automated segregation. The integration of advanced detection techniques with instance segmentation can provide more precise localization of waste objects. Additionally, optimizing the model for edge devices and expanding it to handle multi-object and real-world scenarios will further improve its practical applicability in smart city environments.

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