Automated Trash Classification Using MobileNetV2 for Efficient Waste Sorting

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Abstract:

The growing concerns about environmental pollution and the need for sustainable waste management have led to the development of automated systems for waste sorting. Traditional waste sorting methods rely heavily on manual labor, which is not only time-consuming but also prone to errors. These methods are often inefficient and fail to keep up with the increasing volume of waste produced globally. In response to these challenges, this paper explores the use of deep learning techniques, specifically MobileNetV2, to automate the classification of waste for efficient sorting. The proposed approach utilizes MobileNetV2's lightweight architecture, optimized for mobile devices, to classify various waste types, including plastic, paper, metal, glass, and organic materials. This method can be deployed in real-time waste management systems, offering an efficient, scalable, and environmentally friendly solution. Waste management plays a critical role in maintaining public health and environmental sustainability. As urbanization and industrialization increase, the volume and complexity of waste generated have escalated, creating a pressing need for automated systems that can sort waste efficiently. Machine learning (ML) models, particularly convolutional neural networks (CNNs), have shown great promise in automating image-based tasks, such as object recognition and classification, making them ideal candidates for waste sorting applications. The problem of waste classification is multifaceted, involving the need to accurately identify a wide range of waste materials from images. This is particularly challenging due to the variability in waste items' shapes, sizes, and appearances, as well as the presence of mixed or contaminated waste. Traditional manual sorting methods are insufficient to meet the growing demands for efficient recycling and sustainable waste management. Traditional waste sorting systems primarily rely on human labor or basic mechanical processes such as shredding, screening, and air classification. These systems are labor-intensive, costly, and inefficient, often resulting in contamination of recyclable materials and increased waste sent to landfills. Additionally, these methods are not easily scalable, making them less suitable for dealing with the scale of waste generated by large urban populations.

Keywords: Waste sorting, MobileNetV2, Deep learning, Automated classification, Sustainable waste management, Real-time waste management, Recycling efficiency, Image-based classification, Environmental sustainability

1. INTRODUCTION

The exponential growth of urbanization, industrialization, and population has led to an ever-increasing amount of waste generated globally. Proper waste management and effective sorting of materials are crucial to ensuring sustainability, reducing landfill waste, and promoting recycling. However, traditional waste sorting systems, which often rely on manual labor or basic mechanical processes, are inefficient, error-prone, and labor-intensive. As the world faces growing environmental concerns, there is an urgent need for automated systems that can sort waste materials quickly, accurately, and at scale. In recent advancements in artificial intelligence (AI) and machine learning (ML) have opened up new possibilities for automating waste sorting. MobileNetV2, a lightweight and efficient deep learning model, has gained popularity due to its ability to perform well on mobile and edge devices with limited computational power, making it ideal for real-time image classification tasks, such as waste sorting.

Waste management remains a critical challenge in today's rapidly urbanizing and industrializing world. The traditional waste sorting process, which often involves manual labor or rudimentary mechanical systems, is plagued by inefficiencies, inaccuracies, and high operational costs. Misclassification of waste leads to contamination of recyclable materials, reduced recycling efficiency, and increased strain on landfills, exacerbating environmental degradation. Furthermore, manual sorting exposes workers to hazardous materials, posing significant health risks. The lack of scalable, accurate, and cost-effective solutions has created an urgent need for automated waste sorting systems that can address these challenges. The problem is further compounded by the diversity in waste materials, including paper, plastic, metal, and organic waste, each requiring distinct disposal or recycling methods. To tackle this issue, there is a growing demand for intelligent systems that can quickly and accurately classify waste into predefined categories, ensuring proper recycling and disposal while reducing environmental harm.

The motivation for this research stems from the pressing global need to improve waste management practices and enhance sustainability. Recycling rates remain suboptimal due to the limitations of existing waste sorting methods. With increasing environmental concerns and stringent regulatory frameworks, adopting innovative technologies to optimize waste sorting has become imperative.

Advancements in artificial intelligence (AI) and deep learning, particularly in image classification, present an opportunity to revolutionize waste management. MobileNetV2, a lightweight yet powerful deep learning model, offers the potential to bring intelligent waste classification to mobile and edge devices, making the solution accessible, scalable, and cost-effective. The research aims to leverage this technology to develop an automated waste sorting system capable of handling real-world challenges, such as variations in lighting, object orientation, and material overlap. The project is driven by the dual goal of addressing environmental challenges and showcasing the potential of AI to solve real-world problems, contributing to both technological advancement and ecological sustainability.

2. LITERATURE SURVEY

Waste separation is the key to solving many environmental problems, so residents are encouraged to separate their household waste, but there are so many different types of household waste that many people are unable to properly separate their waste. Initially, people worked to standardize waste separation standards, considering the ease of disposal and carbon footprint [1]. Later, smart bins and kiosks were invented for automatic waste classification [2], but prob-lems such as their poor popularity were also evident. In recent years, the rise of image classification tasks has provided a new direction to solve the garbage classification problem [3].

By using convolutional neural networks to train classification models for a large number of images of household garbage, the obtained models can quickly classify unseen garbage. In order to improve the classification accuracy, the number of network layers has been increased, and the consequent problem is that the size of deep convolutional neural networks is too large to limit the practical applications [4]. Image classification technology uses computers to simulate humans to classify images according to specific rules. It has a wide range of applications in many fields such as medical [5], agricultural, industrial, and service industries. The study of image classification technique includes feature extraction of ideas and classification algorithms for images. The convolutional neuralNET(network) structure is a well-known basic architecture for deep learning in image processing.

Since this NET structure requires fewer training parameters and satisfies a significant interaction of neighboring information when extracting information from an image, different features can be automatically extracted during the processing of the picture. Currently, the classical, familiar convolutional neural NETs used for image feature extraction: are the LeNet [6] NET, the AlexNet [7] NET, the VGGNet [8] NET, and the ResNet [9] NET. In visual analytics, CNNs have an essential position as the basic framework, requiring less algorithmic preprocessing and easy transfer learning, which gives them a place in both image and video recognition [10]. Based on the exploration of NET depth from VGG to ResNet, Densnet [11] explicitly proposed a new deep neural NET architecture to improve the gradient vanishing problem, i.e., connecting all the NET layers while ensuring maximum information transfer among the layers in the NET. However, while different NET architectures tend to explore the NET at a deeper level, there is another group of studies that target different aspects to achieve optimization of the NET across the board. In terms of modularity, GoogLeNet [12], Inceptionv3 [13], Inception-ResNet [14], ResNeXt [15], Xception [16]; in terms of attention, SENet [17], scSE [18], CBAM [19]; in terms of automation, NASNet [20], EfficientNet [21].

The performance of the NET is optimized to a certain after a certain level of performance optimization of the NET, scientific research starts to focus on the computation time of the NET. At this stage, some scientific researches focus on reducing the computational cost of the actual operation of the NET, so there are efficient NETs such as SqueezeNet [22], MobileNet [23], ShuffleNet [24], etc. NETsfor different concerns are available for selection for different application scenarios, and convolutional neural NETs are rapidly developing in the field of image classification.

3. PROPOSED METHODOLOGY

This paper focuses on developing an Automated Trash Classification System using deep learning, specifically leveraging the MobileNetV2 architecture, to classify waste items into categories such as metal, paper, and plastic. The primary objective is to create a system that efficiently and accurately identifies trash types from images, contributing to improved waste management and recycling processes. By integrating computer vision techniques, image classification models, and machine learning algorithms, the system automates the waste sorting process, reducing human effort, minimizing classification errors, and enhancing the efficiency of recycling efforts.

The approach involves building a trash classification model that categorizes images into three classes: metal, paper, and plastic. MobileNetV2, a lightweight deep learning architecture pre-trained on ImageNet, is employed and fine-tuned with a specific trash dataset to improve classification accuracy. Essential preprocessing steps such as image resizing, normalization, and data augmentation are applied to enhance model performance. The training process uses transfer learning, where the initial layers of MobileNetV2 retain their learned features while newly added custom layers are trained for trash classification. The model is evaluated using performance metrics such as accuracy, precision, recall, and F1-score to ensure reliable classification.

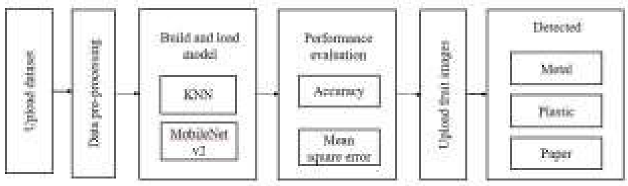

Figure 1: Block Diagram of Proposed System

Figure 1 represents a workflow for a waste classification system using machine learning models. It starts with uploading a dataset followed by data pre-processing. The system builds and loads models, including KNN and MobileNetV2, for classification. Performance evaluation is done using accuracy and mean square error. Users then upload images for classification, and the system detects categories such as metal, plastic, and paper. The process ensures efficient waste sorting using AI-based models.

To highlight the advantages of deep learning, the MobileNetV2-based approach is compared with traditional machine learning algorithms such as K-Nearest Neighbors (KNN), demonstrating improvements in classification accuracy and efficiency. Once trained and evaluated, the model can be deployed in real-world applications, including automated waste sorting systems in recycling centers, trash bins, or waste management facilities. The dataset used for training consists of images categorized into metal, paper, and plastic, organized into training, validation, and test sets for effective generalization. Preprocessing involves resizing images to 64x64 pixels for traditional models and 224x224 pixels for MobileNetV2, normalizing pixel values, and applying data augmentation techniques like rotation, zoom, and horizontal flipping to prevent overfitting.

Model selection is based on MobileNetV2, a pre-trained convolutional neural network (CNN) modified with custom layers for classifying waste items. The model is compiled using the Adam optimizer and categorical cross-entropy loss, which is suitable for multi-class classification. During training, transfer learning is applied, keeping the pre-trained layers frozen while training the new layers. Optimization techniques such as Model Checkpoint, EarlyStopping, and Reduce LROnPlateau ensure efficient learning. After training, model performance is evaluated on a test dataset using accuracy, confusion matrices, precision, recall, and F1-score, with visualization tools like Seaborn aiding in performance analysis.

The system also includes a comparative analysis with the KNN algorithm to validate the effectiveness of deep learning for image-based classification. After successful training and evaluation, the model is ready for deployment in real-time waste management applications, offering an efficient solution for automated trash sorting. MobileNetV2, developed by Google, is designed for mobile and embedded vision applications, providing high performance while being lightweight and computationally efficient. Its architecture incorporates depthwise separable convolutions to reduce computation, inverted residuals to improve information flow between layers, and linear bottlenecks to optimize efficiency. These features make MobileNetV2 suitable for resource-constrained devices such as mobile phones, edge devices, and embedded systems, enabling real-time waste classification with minimal computational overhead.

Applications:

- Used in recycling centers to classify waste efficiently, reducing manual labor.
- Integrated into intelligent bins that automatically sort waste into the correct category.
- Enhances the separation of recyclable materials, improving recycling efficiency.
- Helps cities manage waste effectively by automating sorting at collection points.
- Assists industries in sorting waste materials for proper disposal or recycling.

Advantages:

- Lightweight and Efficient: MobileNetV2 is designed to be computationally efficient, with fewer parameters compared to larger models like VGG16 or ResNet, making it ideal for devices with limited computational power. It uses depthwise separable convolutions and inverted residuals, which reduce the number of operations required for inference, enabling faster processing and lower memory usage.
- High Accuracy: Despite its lightweight nature, MobileNetV2 achieves competitive accuracy in image classification tasks. It is a good tradeoff between performance and efficiency, making it suitable for real-time applications.
- Transfer Learning: MobileNetV2 can be used as a pre-trained model on large datasets (e.g., ImageNet) and fine-tuned on smaller, custom datasets for specific tasks. This helps in leveraging the learned features from a large dataset and reduces the time required for training on a new dataset.
- Flexibility for Mobile and Edge Devices: The architecture is optimized for mobile and embedded systems, making it suitable for real-time applications in resource-constrained environments, such as smartphones, drones, and IoT devices.
- Scalability: MobileNetV2 can be scaled in terms of model size and accuracy by adjusting the width multiplier and resolution multiplier. This allows for a tradeoff between computation, model size, and accuracy based on the available resources.

4. EXPERIMENTAL ANALYSIS

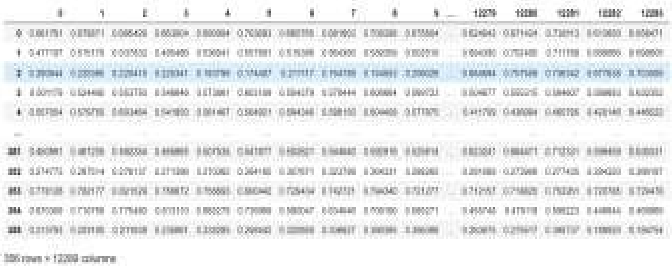

Figure 2: Sample Dataset

Figure 2 shows the dataset consists of 356 rows and 12,289 columns, likely representing image features extracted from a dataset. Each row corresponds to an individual data sample, while each column represents a specific feature or pixel value. The values are normalized between 0 and 1, indicating they might be preprocessed for machine learning tasks. The dataset could be used for classification or predictive maintenance based on extracted image features.

```
Model loaded successfully.
KNN Classifier Accuracy    : 77.77777777777779
KNN Classifier Precision   : 75.56818181818183
KNN Classifier Recall      : 77.4657026325547
KNN Classifier FSCORE      : 74.83039488607074

 KNN Classifier classification report
               precision    recall  f1-score   support

       metal       0.90      0.81      0.85        32
       paper       0.68      0.95      0.79        22
     plastic       0.75      0.50      0.60        18

    accuracy                           0.78        72
   macro avg       0.77      0.76      0.75        72
weighted avg       0.79      0.78      0.77        72
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Figure 3: Classification report of KNN model

Figure 3 shows the K-Nearest Neighbors (KNN) classifier achieved an accuracy of 77.77%, indicating it correctly classified most instances. The precision was 75.56%, meaning that 75.56% of the predicted positive instances were accurate. The recall score of 77.46% shows the model correctly identified 77.46% of all relevant instances. The F1 score was 74.83%, balancing precision and recall.

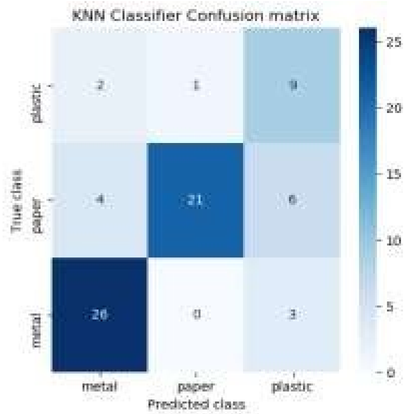

Figure 4: confusion matrix obtained using KNN model

Figure 4 represents a confusion matrix for a KNN classifier, showing the performance of waste classification into metal, paper, and plastic. The rows represent true classes, and the columns represent predicted classes. The diagonal values indicate correct predictions, with 26 for metal, 21 for paper, and 2 for plastic. Misclassifications occur, such as plastic being classified as metal or paper. The model performs well for metal and paper but struggles with plastic classification. The color intensity represents the frequency of predictions.

```
Model loaded successfully.
Found 31 images belonging to 3 classes.
MobileNetV2 Waste Classification Accuracy    : 93.54838709677419
MobileNetV2 Waste Classification Precision   : 94.44444444444446
MobileNetV2 Waste Classification Recall      : 93.63636363636364
MobileNetV2 Waste Classification FSCORE      : 93.6280094174831

MobileNetV2 Waste Classification classification report
              precision    recall  f1-score   support

       metal       0.91      1.00      0.95        10
       paper       1.00      0.83      0.91        12
     plastic       0.90      1.00      0.95         9

    accuracy                           0.94        31
   macro avg       0.94      0.94      0.94        31
weighted avg       0.94      0.94      0.93        31
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Figure 5: Classification report of MobileNetV2 model

Figure 5 shows the MobileNetV2 model achieved impressive performance with an accuracy of 93.54%, demonstrating its reliability in classifying waste materials. The model's precision of 94.44% indicates that it correctly identifies most of the positive instances, reducing the number of false positives. In terms of recall, MobileNetV2 achieved 93.64%, which shows its ability to correctly identify the majority of relevant waste items without missing too many. The F1-score, a balance between precision and recall, stands at 93.63%, reflecting the model's robust performance across all metrics. These results suggest that MobileNetV2 is highly effective for the waste sorting task, providing a good mix of accurate classification and efficient recognition of different waste types.

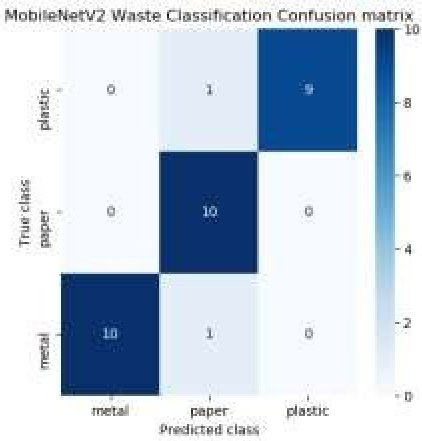

Figure 6: confusion matrix obtained using MobileNetV2

Figure 6 represents a confusion matrix for MobileNetV2 waste classification. It shows true class labels on the y-axis and predicted labels on the x-axis. The model correctly classifies all paper samples but struggles with plastic, often misclassifying it as metal. Metal is mostly classified correctly but has one misclassification as paper. The color intensity represents the number of samples per category.

Figure 7: Predicted image (metal)

Figure 7 shows the model has correctly identified the image as metal, as indicated by the label at the top.

Figure 8: Predicted image (plastic)

Figure 8 shows the model has correctly identified the image as plastic, as indicated by the label at the top.

5. CONCLUSION

The automated waste classification system utilizing MobileNetV2 represents a significant advancement in addressing the challenges of waste management. By leveraging the power of deep learning and lightweight architectures, the project achieves efficient, scalable, and accurate classification of waste materials into categories such as metal, paper, and plastic. This solution minimizes manual effort, reduces sorting errors, and enhances recycling efficiency, contributing to environmental sustainability and public health.

The integration of MobileNetV2 ensures that the system is computationally efficient, making it suitable for deployment on edge devices such as IoT-enabled smart bins or mobile applications. This democratizes access to intelligent waste sorting technology, allowing for widespread adoption in urban and rural settings alike. The implementation also highlights the potential of AI in solving real-world problems, setting a benchmark for future innovations in waste management and other critical industries. In conclusion, the project not only addresses immediate waste sorting challenges but also provides a foundation for further research and development in environmentally conscious technologies.

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