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Deep Learning-Based Approaches for Electronic Waste Detection and Classification: A Step Toward Sustainable Recycling

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The proper management of electronic waste (e-waste) is of critical importance for environmental and economic sustainability. Classifying waste according to its type is considered one of the effective solutions to mitigate the impacts of environmental pollution and ensure a sustainable standard of living. Incorporating sorted waste into recycling processes enables the conservation of natural resources and their reintegration into the production cycle. Traditional waste management methods are generally based on manual classification and physical detection technologies. In the manual classification of e-waste, the type of waste is determined by its physical properties or chemical analysis. These methods are time-consuming, costly, and prone to human error. The limitations of traditional waste management methods necessitate the use of deep learning-based approaches. In this study, a deep learning-based method is proposed to detect the types of e-waste. The study employs three different feature extraction architectures (EfficientNetB0, Inceptionv3, and AlexNet) and five different classification algorithms to identify e-waste types. System performance was evaluated using metrics such as Accuracy, Precision, Recall, and F1-Score. Experimental results indicate that the highest performance was achieved with the EfficientNetB0+SVM, Inceptionv3+SVM, and Inceptionv3+LR combinations, with the highest accuracy recorded at 97%. The results are presented in tabular form, demonstrating that deep learning-based approaches offer an effective solution for e-waste management. This study highlights the innovative and practical potential of deep learning in the detection and classification of e-waste.

Key words: *Deep Learning, e-Waste Detection, Waste Management, Waste types,*

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1. Introduction

The proper management of electronic waste (e-waste) is a critical environmental and economic issue driven by increasing digitalization and technological advancements. Globally, millions of tons of e-waste accumulate annually, and the hazardous substances contained in these wastes pose significant threats to both the environment and human health. On the other hand, recovering valuable metals from e-waste and properly disposing of toxic materials require an effective management system. In this context, deep learning-based solutions for the automated detection and classification of e-waste are crucial for improving the efficiency of recycling processes and minimizing environmental impacts [1-3].

The accurate identification of e-waste provides both environmental and economic benefits. Properly managed e-waste prevents the release of toxic substances into the environment, thereby protecting ecosystems. Moreover, recovering valuable metals from e-waste supports circular economy practices by reducing the consumption of natural resources. However, errors in detection processes can negatively impact the efficiency of the recycling chain, emphasizing the importance of accurate and fast detection [4].

Traditional waste management methods predominantly rely on manual classification and physical detection technologies. Currently, environmental waste is collected on a daily basis by waste collection vehicles and is manually sorted in waste separation centers before a portion of it is subjected to recycling. In manual classification, the type of waste is identified based on its physical properties or chemical analyses. These methods are time-consuming, costly, and prone to human error. In contrast, deep learning methods can process large visual datasets to perform the same tasks more quickly and cost-effectively. With such systems, waste categories can be directly processed at environmental recycling centers after collection. This approach improves and advances the management and operation of environmental waste, contributing to a more sustainable world and the preservation of biodiversity [5].

The classification of environmental waste using image processing methods has become a significant area of research in recent years [5]. Several studies in the literature have demonstrated the potential of advanced deep learning architectures for e-waste classification. For example, EfficientNet-D2 has achieved an accuracy rate of 82.32% in classifying e-waste types [6], and Sequential Neural Network (SNN) models have achieved a remarkable 100% accuracy [7]. Additionally, lightweight systems such as the MobileNetV2-SSD model have been developed for the classification of materials like metal and plastic [8]. Robotic technologies integrated with deep learning algorithms have facilitated the automated collection and classification of e-waste. A robotic system based on YOLOv5 has been able to identify plastic e-waste with 92.1% accuracy in real time [9]. These studies highlight the effectiveness of deep learning methods in e-waste detection.

In this study, an autonomous system is proposed to prevent recyclable waste from accumulating in the environment and becoming hazardous. The study aims to detect ten types of e-waste, including batteries, keyboards, microwaves, phones, mice, printed circuit boards, media players, printers, televisions, and dishwashers. The proposed system is designed using deep learning-based image recognition models to accurately classify each type of waste by analyzing its visual features. The study employs three deep learning-based feature extraction architectures and five different classifiers. The proposed system can be integrated with portable devices for use in real-world applications, enabling real-time implementation. Additionally, such systems have the potential to increase automation in recycling processes, reduce costs, and minimize human labor.

The remainder of the paper is organized as follows: Section 2 provides detailed information on the dataset and methods used in the study. Section 3 presents the experimental results in tabular form, followed by a comparative analysis of the outcomes. The conclusion summarizes the findings of the study.

2. Materials and Methods

In this section, information about the dataset and methods used in the study is presented.

2.1. Materials

The study utilized an open-source dataset obtained from the Kaggle platform [10]. This dataset is specifically designed for the visual classification and analysis of e-waste. It consists of ten e-waste classes: batteries, keyboards, microwaves, phones, mice, printed circuit boards, media players, printers, televisions, and dishwashers. Each class contains 300 images, resulting in a total of 10,000 image samples. The dataset is divided into three groups: training, testing, and validation. The images in this dataset were collected from various sources, including open datasets, image repositories, and proprietary resources [10].

2.2. Methods

In this study, three different feature extraction architectures and five classification algorithms were employed for the detection of e-waste. The operational architecture of the proposed system is presented in Figure 2.1.

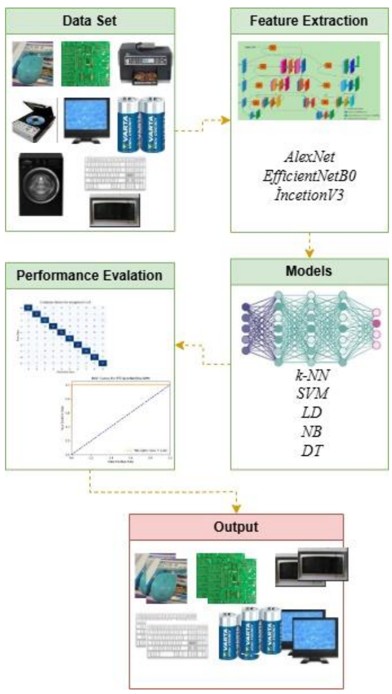


Figure 2.1. Workflow of the Proposed System

The proposed system begins with the processing of a dataset comprising various images representing e-waste categories. Advanced deep learning models, such as AlexNet, EfficientNetB0, and InceptionV3, were utilized for feature extraction to derive meaningful characteristics from the images. Subsequently, the extracted features were fed into machine learning algorithms, including k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Naive Bayes (NB), and Decision Tree (DT), for classification purposes.

The performance of the models was evaluated using metrics such as Accuracy, Precision, Recall, and F1-Score, derived from the results of the confusion matrix and ROC curves. The classification accuracy was thoroughly analyzed. The results demonstrate that e-waste types were successfully classified, highlighting the potential of this approach for optimizing recycling processes and promoting environmental sustainability.

2.3. Performance Evaluation

The confusion matrix is a tool used to analyze the performance of a model in greater detail. Metrics such as accuracy, precision, recall, and F1-score, calculated from the confusion matrix, play a significant role in evaluating classification models. Using these metrics together in research and applications allows for a more comprehensive analysis of model performance. Each of these metrics enables the analysis and improvement of different aspects of a model.

Accuracy reflects the overall success rate of the model, while precision is important for minimizing the impact of false positive predictions. Recall assesses the model's capacity to identify all positive instances. Finally, the F1-score emerges as a balanced measure of model performance, particularly in cases where both precision and recall are crucial [11]. Figure 2.2 presents the confusion matrix.

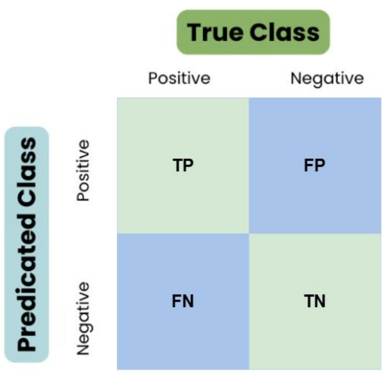


Figure 2.2 Confusion Matrix

Figure 2.2 defines the classes of the confusion matrix with four components:

- True Positive (TP): Correct positives (actual positive and correctly predicted).
- False Positive (FP): Incorrect positives (actual negative but predicted as positive).
- False Negative (FN): Incorrect negatives (actual positive but predicted as negative).
- True Negative (TN): Correct negatives (actual negative and correctly predicted).

3. Experimental Results and Discussion

In this study, feature maps of e-waste images were generated using AlexNet, EfficientNetB0, and InceptionV3 architectures. The obtained feature maps were classified using k-NN, SVM, NB, LDA, and DT algorithms to propose a system for detecting e-waste types. Model performance was evaluated using metrics such as accuracy, precision, recall, and F1-score. The results are presented in Table 3.1.

Table 3.1. Experimental Findings

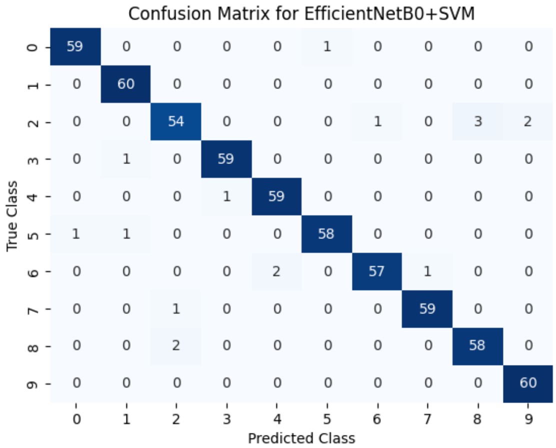
Models	**Classifiers**	**Performance measurement**			
		A	***P***	***R***	***F***
AlexNet	**LR**	0.92	0.91	0.92	0.91
	kNN	0.89	0.89	0.90	0.89
	NB	0.85	0.85	0.85	0.85
	SVM	0.92	0.92	0.92	0.92
	DT	0.73	0.73	0.73	0.73
EfficientNetB0	**LR**	0.96	0.96	0.96	0.96
	kNN	0.94	0.94	0.94	0.94
	NB	0.92	0.91	0.92	0.92
	SVM	**0.97**	**0.97**	**0.97**	**0.97**
	DT	0.81	0.81	0.81	0.81
Inceptionv3	**LR**	**0.97**	**0.97**	**0.97**	**0.97**
	kNN	0.94	0.94	0.94	0.94
	NB	0.92	0.92	0.93	0.92
	SVM	**0.97**	**0.97**	**0.97**	**0.97**
	DT	0.81	0.81	0.81	0.81

A:Accuracy, P:Precision, S:Sensibility, F:F Skor

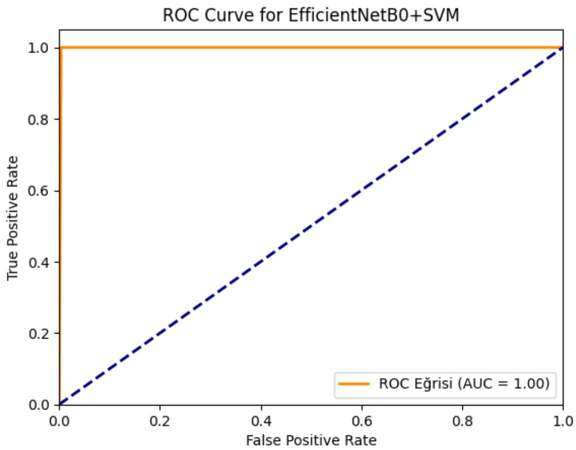
Table 3.1 reveals that the performance of each model varies depending on the classifier used.

In this study, the performances of deep learning-based CNN models such as AlexNet, EfficientNetB0, and Inceptionv3 were compared using different classifiers, including Logistic Regression (LR), k-Nearest Neighbor (kNN), Naive Bayes (NB), Support Vector Machines (SVM), and Decision Trees (DT). The comparison was conducted using metrics such as accuracy, precision, recall, and F1-score. The results indicate that the choice of model and classifier plays a critical role in the classification performance.

Figure 3.1 below presents the Confusion Matrix and ROC Curve for the EfficientNetB0 + SVM model.



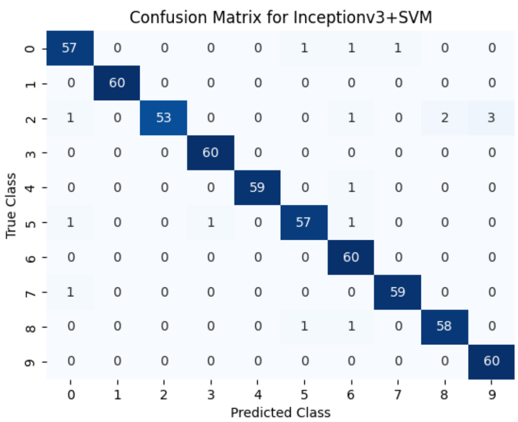
a) Confusion Matrix



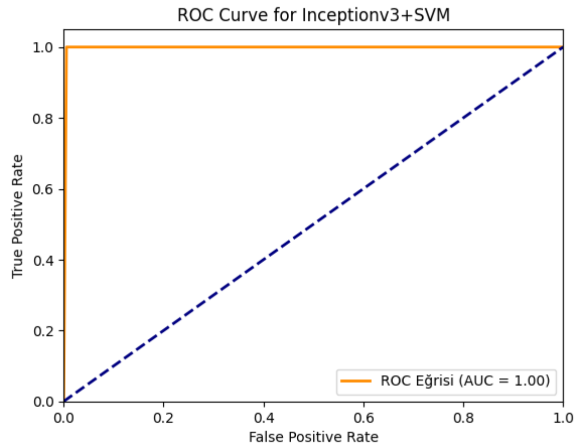
b) ROC Curve

Figure 3.1 a) Confusion Matrix and **b)** ROC Curve for the EfficientNetB0 + SVM Model

Figure 3.2 presents the Confusion Matrix and ROC Curve for the Inceptionv3 + SVM model.



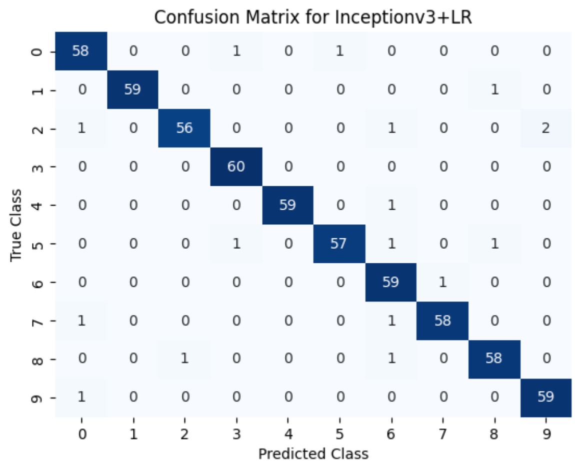
a) Confusion Matrix



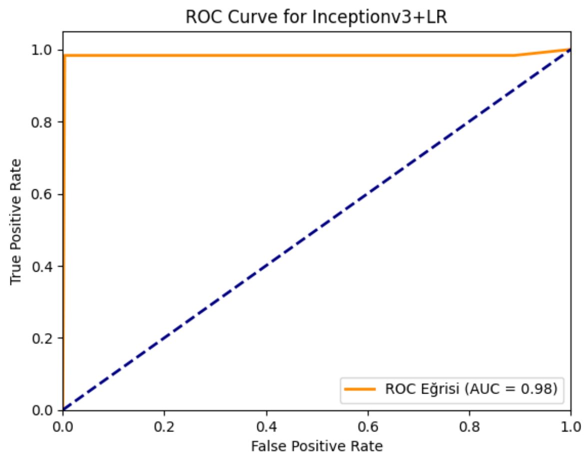
b) ROC Curve

Figure 3.2 a) Confusion Matrix and **b)** ROC Curve for the InceptionV3 + SVM Model

Figure 3.3 presents the Confusion Matrix and ROC Curve for the InceptionV3 + LR model.



a) Confusion Matrix



b) ROC Curve

Figure 3.3 a) Confusion Matrix and **b)** ROC Curve for the InceptionV3 + LR Model

EfficientNetB0 and Inceptionv3 generally achieved the highest performance values, particularly when combined with SVM, yielding an accuracy of 0.97 and an F1-score between 0.97 and 0.97. AlexNet, as an older model, achieved reasonable results with LR and SVM (accuracy: 0.92 and 0.92); however, it demonstrated relatively lower performance in other metrics and classifiers. Decision Trees (DT) emerged as the lowest-performing classifier across all three models. Consequently, SVM and LR stand out as reliable classifiers for complex data structures, while EfficientNetB0 and Inceptionv3 have proven to be high-performing alternatives among deep learning models and are considered strong candidates for such tasks. Key highlights of the study:

- The proposed system can contribute to increasing recycling rates.
- While improper management of e-waste harms the environment, more accurate detection and classification using deep learning models can help mitigate environmental impacts. This can pave the way for new approaches within the framework of sustainable technology management and a circular economy.
- The study compares the performance of different feature architectures with various classifiers, offering insights into architecture-classifier compatibility that can guide future research.

This study has certain constraints and limitations, with potential challenges regarding the generalizability and applicability of the results. Limitations of the study:

- Labeling datasets for deep learning models is typically time-consuming and costly. The number and variety of data used in this study are limited. Increasing the diversity and number of e-waste types could improve system performance in future studies.
- E-waste mixed with complex backgrounds or other waste types can reduce the accuracy of image processing-based models.
- The types, quantities, and compositions of electronic devices used in different regions vary based on socioeconomic conditions, technological infrastructure, and consumer behavior. Due to regional differences in e-waste types, the proposed model’s generalizability may be limited.

Results

Environmental pollution is a critical issue that harms nature and poses a significant threat to our lives today. This problem arises from the careless disposal of waste into the environment and its prolonged presence without degradation. Sorting waste by type is considered an effective solution to mitigate the impacts of environmental pollution and ensure a sustainable standard of living. Incorporating sorted waste into recycling processes enables the conservation of natural resources and their reintegration into the production cycle. This recycling-focused approach not only contributes to making the environment a more livable place but also fosters environmental awareness among individuals, encouraging more responsible consumption and waste management practices. In the detection and management of e-waste, deep learning technologies offer a significant opportunity in terms of environmental sustainability and resource efficiency. Compared to traditional methods, deep learning algorithms provide higher accuracy and speed. In this study, the performances of deep learning-based CNN models, including AlexNet, EfficientNetB0, and Inceptionv3, were evaluated using various classifiers such as Logistic Regression (LR), k-Nearest Neighbor (kNN), Naive Bayes (NB), Support Vector Machines (SVM), and Decision Trees (DT). The performance metrics used in the evaluation included accuracy, precision, recall, and F1-score. The results demonstrated that the choice of model and classifier plays a crucial role in classification success. EfficientNetB0 and Inceptionv3 outperformed other models, achieving accuracy values of 0.97 when combined with SVM and LR classifiers. These findings indicate that EfficientNetB0 and Inceptionv3, particularly when integrated with robust classifiers like SVM and LR, offer effective solutions to classification problems.

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