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Environmental impacts in e-waste management using deep learning

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Abstract
This paper introduces a robust neural network framework to address the environmental difficulties of e-waste management by combining EfficientNet, MobileNet, and a Sequential Neural Network (SNN) for effective classification and sorting of different e-waste categories. The suggested model showed an impressive 98% accuracy, with precision, recall, and F1-scores of 98%, 97%, and 97%, respectively, surpassing standalone models such as MobileNet (86%), EfficientNet (85%), and Yolov8 (88%). ROC analysis demonstrated exceptional performance, with an AUC of 1.00 for all classes. Advanced preprocessing techniques, including SMOTE and data augmentation, ensured dataset balance and improved model generalization. The framework addresses challenges like feature overlap between classes and demonstrates scalability and adaptability for real-world applications. This innovative approach enhances recycling efficiency and promotes environmental sustainability, providing a pathway for deploying AI-driven solutions in e-waste management.

Keywords E-waste sorting · Hybrid model · Multi-class classification · Recycling efficiency · Environmental sustainability

1 Introduction

The deep learning system for managing e-waste is an emerging technology that combines technological and environmental sustainability in the digital era. Observing every little thing on our hectic schedules cannot handle this issue. Nowadays, people choose automatic systems over manual ones to simplify and ease life in all respects [1]. Even so, it is commonly accepted that garbage disposal solutions are essential and should be provided in every community. The consequences and harm caused by inadequate waste management are hazardous to the world and human health. It has served as a wake-up call to investigate the satiation before it causes even more harm to the world at large [2]. Nevertheless, very little is known about what constitutes e-waste. This has made it necessary to search for the best method to manage the waste appropriately by classifying the waste components using the newest technological advancements [3]. The idea as it is currently presented is a revolutionary way to deal with the growing difficulties associated with managing e-waste [4]. The concept integrates cutting-edge technologies, primarily artificial intelligence to optimize waste management processes.

The use of electrical and electronic equipment (EEE) is growing at a rapid rate, and as a result, e-waste is becoming a major global environmental problem. Numerous research studies have indicated that improper recycling methods for e-waste can result in hazardous materials being present, which can pose health risks to humans and cause environmental catastrophes [1]. This research focuses on the development of an intelligent automated sorting system that uses a deep learning algorithm [5]. Due to its innovation, which will make sorting safe and rapid, this will eliminate the need for sorting

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and prevent exposure to dangerous substances that harm the environment and soil [6]. This technologically advanced approach aims to revolutionize e-waste management by providing a long-term, affordable solution. It is anticipated to boost the use of e-waste recycling bins, supporting initiatives and fostering a cleaner, safer, and greener environment by monitoring and managing the intelligent collection, segregation, and disposal of e-waste through the application of deep learning (DL) [7]. The environmental threat posed by the growing amount of electronic waste, or "e-waste,"" is exacerbated by the shortcomings of conventional manual sorting techniques [8]. To increase the precision and effectiveness of e-waste management [9], this work presents a novel deep learning system for automated e-waste sorting using a hybrid framework. The model was trained using a large dataset of e-waste components, which included circuit boards, batteries, mobile devices, washing machines, printers, keyboards, televisions. The dataset underwent rigorous preprocessing. Convolutional layers were used in the network to extract features, and then pooling and dropout layers were used to get fully connected layers and a softmax output for multi-class classification. In this work, we present a novel approach to e-waste sorting by integrating MobileNet and EfficientNet with a Sequential Neural Network (SNN) architecture. This combination leverages the efficient feature extraction capabilities of MobileNet and EfficientNet while maintaining the adaptability of SNN for multi-class classification tasks. Unlike previous studies that focus on general waste management or use a single deep learning model, our approach specifically addresses the unique challenges of e-waste, including the variability in material composition and form factors. The proposed system is optimized for real-world application in recycling facilities, demonstrating superior accuracy and efficiency compared to existing methods. The system's performance demonstrates how reliable and practically applicable it can be, greatly increasing the efficiency of sorting e-waste and promoting environmental sustainability.

2 Literature review

The literature review presents a comprehensive overview of the current state of research in electronic waste (e-waste) management, particularly focusing on applying deep learning technologies [10]. E-waste is increasingly recognized as a significant global environmental issue, with improper disposal leading to hazardous material release and health risks [11]. The review highlights the need for innovative solutions to enhance e-waste classification and management processes, emphasizing the limitations of traditional methods that often rely on manual sorting and outdated technologies [12]. Several studies have explored the potential of artificial intelligence (AI) in waste management, but specific research addressing e-waste remains limited. For instance, previous work has demonstrated the application of AI and robotics to improve e-waste collection and segregation, aiming to automate hazardous processes and alleviate the burdens laborers face in this field. However, these studies often lack detailed methodologies for training and validating AI algorithms, indicating a gap in the literature regarding the scalability and accuracy of existing approaches [13]. The review also discusses various methodologies employed in e-waste management, including the use of mechatronics and machine learning for recycling processes, and the development of IoT-based monitoring systems to support smart city initiatives. While these approaches show promise, they often fail to provide comprehensive solutions that integrate advanced machine-learning techniques with practical applications in recycling facilities [14]. Research gaps identified include the need for more detailed information on specific technologies and processes, as well as the integration of advanced algorithms to improve efficiency and accuracy. Bagwan [15] explores electronic waste (E-waste) management in Maharashtra, India, using ARIMA forecasting to analyze trends and predict future recycling capacities and the number of recyclers up to 2030. The study emphasizes the importance of a circular economy framework to enhance sustainable practices, mitigate environmental risks, and create job opportunities. Data collected from peer-reviewed literature and official reports form the basis of the analysis, with ARIMA modeling providing robust predictions. Strengths include reliable forecasting, a focus on resource restoration, and economic benefits, while limitations involve forecasting accuracy and data reliability. Research gaps highlight the need to integrate informal recycling practices and develop locally tailored policies. Dataset limitations include biases in secondary data, restricted diversity, and inadequacy in capturing emerging trends, underscoring the need for further research to address these challenges and improve E-waste management practices. Goyal and Gupta [16] examines e-waste management in Canada, focusing on analyzing collection trends across provinces and evaluating the cost-effectiveness of stewardship programs from 2013 to 2020 using EPRA reports. The study compares industry characteristics, expenditures, and per capita collection trends across six provinces, providing data-driven insights into regional stewardship models. Strengths include its originality in assessing stewardship attributes at a regional level, comprehensive analysis across jurisdictions, and emphasis on inter-provincial collaboration. Limitations involve incomplete stakeholder inclusion, variability in program coverage, and potential biases from the timeframe of data. Research gaps highlight the need for region-specific strategies and exploration of diverse e-waste categories, including their recycling efficiency and product design impacts. Dataset limitations include sensitivity to bulky items, underreporting of non-EPRA-managed e-waste, and challenges in understanding due to staged implementation projects. The study underscores the importance of tailored approaches to improving e-waste management systems across Canada. Dodampegama et al. [17] explores how AI and robotics can improve sorting processes for construction and demolition (C&D) waste, supporting sustainable practices and circular economy principles. Using bibliometric and scientometric analysis, the study reviews key aspects of AI applications, sensor technologies, robotic roles, and challenges in the field. Strengths include the integration of advanced techniques like multisensory data fusion and unsupervised machine learning, along with a strong emphasis on sustainability. However, limitations such as the complexity of C&D waste and limited implementation of robotic systems are noted. Research gaps emphasize the need for large-scale, multisensory datasets and innovative AI methods like transfer and unsupervised learning. Dataset limitations include scarcity, reliance on RGB images without depth information, and insufficient support for advanced tasks like segmentation. The study highlights the urgency for improved datasets and AI methodologies to advance waste management practices [18]. The document proposes an automatic e-waste management system for Nepal using machine learning algorithms, aiming to enhance the efficiency of e-waste handling and improve prediction and classification accuracy. The methodology combines deep learning techniques like Convolutional Neural Networks (CNN) for feature extraction and Restricted Boltzmann Machines (RBM) for accuracy enhancement, with preprocessing through Niblack's algorithm. An open-source Kaggle dataset, split into training and testing sets, is used for validation. Strengths include achieving 96% classification accuracy, employing a novel deep learning approach, and benchmarking against models like ResNet50 and VGG16. However, limitations include dependency on dataset quality, generalization issues, and restricted applicability to limited e-waste types. Research gaps emphasize the need for localized studies on Nepal's e-waste challenges and exploring advanced architectures for improved results. Dataset limitations involve varying image quality, insufficient diversity, and limited size, which may affect the model's robustness. The study provides a promising direction for e-waste management but identifies areas for further enhancement [19]. The research focuses on enhancing disaster waste management through the development of the He-DWS model, an AI-based system designed to classify various waste types in disaster scenarios. Using a dual ensemble deep learning framework, the study integrates diverse image segmentation methods and CNN architectures. It employs data augmentation techniques to improve dataset variability and robustness and evaluates the model across three datasets, including TrashNet and two real-world flood-related datasets. The model's strengths lie in its innovative framework, comprehensive evaluation, and effective use of AI for complex classification tasks. However, it faces challenges such as computational complexity and reliance on data quality. Research gaps include the need for lightweight, efficient models and optimization for resource-constrained environments. Dataset limitations, like data scarcity and under sampling, hinder the model's generalization and real-world applicability. To address these, strategies such as data augmentation, collecting diverse data, generating synthetic data, cross-dataset training, balancing datasets, and continuous updates are recommended, ensuring improved robustness and relevance for disaster waste management [20]. The study aims to address the E-waste challenges in South Asia by analyzing its generation, management, and hazardous impacts, focusing on the social, environmental, and economic aspects of recycling and proposing sustainable management strategies. Utilizing a three-phase methodology, the research draws on secondary data for a comparative analysis of E-waste consumption, import, and recovery processes across South Asian countries. Its strengths include a comprehensive review of regional practices and a focus on sustainability, with practical proposals for regulation and monitoring. However, the study faces limitations due to data scarcity, especially in underdeveloped countries, and the exclusion of manufacturing phases in Life Cycle Assessments (LCA). Research gaps include the need for more region-specific studies, particularly in underrepresented areas, and the limited scope of LCA studies in developing countries. Dataset limitations arise from the lack of a formalized E-waste management sector and variability in data quality, which can affect the reliability of the findings [21]. The study aims to introduce novel resilience assessment methodologies for e-waste management systems and provide policy recommendations that align practices with sustainability goals, including carbon neutrality. Utilizing Bayesian Network (BN) modeling, the research assesses the adaptability and responsiveness of these systems, incorporating expert input and conducting analyses like forward and backward propagation, information theory, and sensitivity analysis. The study's strengths include its innovative approach to understanding system dynamics, practical policy recommendations, and emphasis on stakeholder engagement. However, limitations include potential biases in expert judgment, lack of uncertainty handling for input data, and a focus on subjective assessments, which may affect reliability. Research gaps include exploring Circular Economy (CE) principles in e-waste management and investigating the role of technology and stakeholder partnerships. Dataset limitations are tied to the reliance on subjectiveexpert opinions, which may introduce variability and uncertainty, suggesting the need for additional data sources for validation [22]. The study aims to use Artificial Neural Networks (ANN) to predict the gravimetric composition and specific weight of Municipal Solid Waste (MSW), especially during disruptions like pandemics when data collection is limited. The methodology modifies an existing theoretical model to incorporate socioeconomic indicators and historical data, with predictions showing high accuracy (less than 10% error for most fractions). The model's strengths lie in its versatility, efficiency, and high predictive accuracy, while limitations include dependence on data quality and higher errors for specific waste fractions. Research gaps include improving data collection methods during disruptions and testing the model across different contexts. Strategies to address dataset limitations include enhancing data validation, improving collection methods, updating datasets, broadening geographic applications, and conducting error analysis. These improvements would help make the model more reliable and applicable to various situations [23]. The study investigates the role of artificial intelligence (AI) in waste management, aiming to enhance decision-making, optimize processes, and promote sustainability. A comprehensive literature review was conducted, analyzing 71 articles published between 2021 and 2023. Key strengths include a detailed synthesis of recent advancements and a focus on stakeholder collaboration to improve data sharing and standardization. However, limitations such as data privacy concerns, fragmentation due to non-standardized formats, and insufficient centralized platforms hinder effective implementation. Research gaps highlight the need for better data collection methods, enhanced integration of IoT devices for real-time data, and improved protocols for data quality and accessibility. Additionally, challenges such as data availability, accuracy, and privacy issues must be addressed to maximize the reliability and effectiveness of AI-driven waste management solutions [24]. The research in waste and e-waste management aims to develop sustainable solutions for environmental pollution, enhance recycling technologies, and promote intelligent systems for improved decision-making. Methodologies employed include machine learning for waste prediction, Analytic Hierarchy Process (AHP) for prioritizing solutions, and case studies to evaluate strategies. The strengths of this field involve the integration of advanced technologies like IoT and blockchain, which enhance transparency and efficiency. However, challenges such as inconsistent data quality, high implementation costs in developing regions, and complex system integrations persist. Research gaps include the need for studies on socio-economic impacts, long-term sustainability of technologies, and public awareness regarding waste management. Additionally, datasets may suffer from biases and temporal limitations. Overall, the study emphasizes the importance of innovative approaches to improve e-waste management practices while addressing environmental concerns [25]. The study aims to enhance e-waste recycling by developing an AI-based decision support system that uses fuzzy logic to evaluate the recycling potential of electronic products based on parameters like material, weight, and dimensions. The system is supported by a database (VEIDD) that collects product information and adapts over time through continuous learning. While the system's adaptability and simplicity are strengths, its effectiveness is limited by data quality, incomplete product details, and the complexity of some e-waste types. The research highlights the need for more comprehensive data, expanded applications, and the inclusion of environmental and economic factors in the decision-making process [19]. The research focuses on enhancing solid waste management (SWM) by applying artificial intelligence (AI) and Internet of Things (IoT) technologies. Its objectives include improving waste management sustainability and efficiency through AI, specifically using ensemble learning and DenseNet121 for waste classification while leveraging IoT for real-time monitoring. Strengths of the study include increased prediction accuracy and operational efficiency, as well as better decision-making through IoT integration. However, limitations include the cost of implementation, challenges with existing infrastructure, and dataset issues such as limited diversity and data quality concerns. The research highlights the need for further studies on the long-term sustainability of AI in SWM and explores gaps in the generalizability of AI models across different contexts. The potential of AI in waste management has been demonstrated in previous research across a range of applications, including optimization of recycling and sorting municipal solid waste. However, there is a lack of studies specifically focused on the management of e-waste. In current methodologies, traditional machine learning algorithms are frequently employed, but they may not provide the necessary scalability and precision [26]. The research utilized artificial intelligence and robotics to improve the gathering and sorting of electronic waste in India. Its objective was to automate the dangerous procedures and alleviate workers from their perilous work conditions. Existing gaps in research include insufficient information regarding the training and verification of AI algorithms for identifying waste. Future developments involve enhancing the robot's payload capacity to accommodate larger appliances [27]. The research introduced an automated solution for e-waste recycling that utilizes deep learning. It emphasized the possibilities for effective component extraction. Existing gaps in research include insufficient details regarding the specific technologies and procedures employed. Future efforts will focus on incorporating more sophisticated machine learning algorithms and computer vision methods to improve efficiency and precision [28]. The research introduced an IoT e-waste tracking system to aid smart city projects. It employed an agile methodology to allow for flexible and responsive development. Identified research gaps encompass the potential for scope creep or feature creep arising from the iterative process of the methodology. Upcoming efforts aim to enhance the system's ease of use through push email functionality and to create an Android application [9]. The study utilized a transformer-based machine learning technique to tackle the challenges of sustainable e-waste management. It applied different efficiency strategies, conducted comparative policy assessments, and employed data analysis techniques to investigate e-waste management systems. Recognized research deficiencies underscore the lack of a unified framework that connects e-waste management with urban sustainability. Future research will aim at refining engines to improve the performance and efficiency of biofuels generated from plastic waste [29]. The research established an effective monitoring system for fill levels in smart e-waste recycling. It employed an ultrasonic sensor as the main device for assessing fill levels and a temperature sensor for tracking the temperature within the bin. Existing research gaps include the absence of a GPS module for tracking the bin's location. Future developments aim to create predictive maintenance features based on past fill levels and usage trends [30]. The research examined abandoned computers in Benin City, acquired discreetly from different sources, and surveyed to gauge user preferences before the disposal of used computers. The goals of the paper include identifying methods for effectively erasing hard drives before disposal, carrying out a survey on the data security of electronic waste, and creating a data security framework for managing e-waste. The limitations of this study include not addressing data security concerns related to e-waste, the lack of a recycling facility in the area, and insufficient technical information. The identified research gap in this paper is the insufficient focus on data security in e-waste management, which is a vital issue that must be tackled [31]. The approach involves a cross-sectional research methodology and the use of structured questionnaires for data collection. This paper aims to pinpoint the difficulties associated with e-waste management in African countries. The study's limitations include dependence on self-reported information and conduct within a single geographical area. Its strengths are characterized by the empirical research carried out with a substantial sample size. Identified research gaps suggest a necessity for future investigations into intelligent recycling systems and sorting technologies. The future direction of this paper focuses on suggesting a framework to enhance and optimize e-waste management processes and data security, ultimately leading to improved environmental practices and data safeguarding. Recent advancements in deep learning, particularly in convolutional neural networks, now provide opportunities to refine e-waste categorization systems. Recent research has increasingly employed deep learning techniques to enhance e-waste management, achieving notable improvements in classification accuracy and operational efficiency. Convolutional Neural Networks (CNNs) have proven particularly effective in classifying e-waste components, such as circuit boards, batteries, and other electronic parts, based on their visual characteristics. These capabilities areessential for developing automated sorting systems for recycling facilities. A significant advancement in this domain is the integration of models like MobileNet and EfficientNet with Sequential Neural Networks (SNNs). These hybrid architectures combine efficient feature extraction with adaptability for multi-class classification tasks, resulting in superior performance. For instance, a recent study achieved 98% classification accuracy using such a hybrid model, surpassing standalone models. Additionally, AI-driven robotic systems have been developed to automate the collection and segregation of e-waste, identify hazardous materials, and improve recycling efficiency. However, a lack of comprehensive methodologies for training and validating these AI systems highlights gaps in scalability and accuracy. Current datasets present challenges that hinder further advancements. Many are small, lack diversity, or are poorly annotated, focusing primarily on common components like batteries and circuit boards while neglecting less common items such as mobile devices. This limits the models' ability to generalize to new or unseen categories. Real-world complexities, such as mixed or disassembled e-waste items, are also underrepresented. To address these limitations, a new dataset comprising over 3000 images of diverse e-waste components has been introduced. It includes a wide range of items which include circuit boards, batteries, mobile devices, washing machines, printers, speakers, keyboards, mice, televisions, computers microwaves, and players to provide a representative sample for training deep learning models. Rigorous preprocessing techniques, including normalization and data augmentation, were applied to enhance data quality and improve model robustness, paving the way for more effective e-waste management solutions.

3 Materials and methods

The proposed methodology for addressing e-waste management through deep learning is a hybrid model that integrates MobileNet, EfficientNet, and a custom Sequential Neural Network (SNN), designed for efficient sorting of e-waste in resource-constrained environments [13]. The architecture utilizes a hierarchical block structure that includes four parent classes and their respective child classes, enabling fine-grained classification [27]. The dataset consists of over 3000 images, categorized into 12 types of e-waste, with preprocessing steps such as resizing, bounding box extraction, and data expansion techniques applied to enhance model robustness [28]. The model was trained for 20 epochs; the dataset is divided into 82% for training and 18% for testing and validation. The loss function used is Categorical Cross-Entropy, with hyperparameters optimized for performance. Notably, the model features dynamic selection between architectures based on task requirements and computational resources, alongside real-world scalability, making it suitable for deployment in recycling facilities. Evaluation metrics include accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC, with the hybrid model outperforming SNN, MobileNet, EfficientNet, and yolov8 in terms of accuracy. This

Fig. 1 Dataset images of e-waste categories

innovative approach ensures adaptability, scalability, and practical deployment, providing an effective solution for the challenges of e-waste sorting and management. The methodology's emphasis is on hierarchical classification, dynamic architecture integration, and real-world application.

3.1 Data collection

The E-Waste Dataset is a collection of images representing electronic waste items categorized into distinct classes. The dataset is designed for tasks such as image classification, object detection, and other computer vision applications. Electronic waste, or e-waste, is a growing concern globally, and this dataset aims to contribute to the development of technology-driven solutions for its management and recycling [31]. The dataset used for this research was collected from the Kaggle online dataset repository. The training data was obtainable and was mainly used in sorting e-waste for recyclability status, classified as battery, computer, keyboard, mouse, printer, washing machine, PCB, player, microwave, mobile, television, and speaker. Twelve different product categories make up the dataset, and the total number of items is split up into three subsets: training, testing, and validation. There are 3859 items in total across all categories, with the training set including the majority (3139 pieces). Given that a model needs a significant amount of data to learn efficiently, this makes sense because training data usually makes up the greatest chunk of machine learning. There are 360 items in each of the testing and validation sets, with 30 items distributed consistently throughout each category. Without favoring any one class over another, this equitable distribution of testing and validation data guarantees that the model can be assessed and adjusted uniformly across all categories. When we examine the individual categories, we find that the training data differs slightly, with the Speakers category having 246 items and the Mobile and Printer categories having 270 things. These differences can be due to the complexity of each product category or the data that is available for it. The testing and validation sets, which consist of 30 items each, are uniform across all categories. The consistency of testing and validation data guarantees impartiality and equilibrium when assessing the model's performance in every category, irrespective of the overall quantity of training objects. They were processed, trained, tested, and evaluated for performance [32]. Dataset preprocessing is critical for improving model performance and reliability. To address class imbalance, techniques such as oversampling minority classes, under-sampling majority classes, and using synthetic data generation methods like SMOTE were applied to ensure balanced representation across categories [33]. Data augmentation methods, including rotation, flipping, scaling, and color adjustments, were employed to improve the variety of the training data., enhancing model generalization by exposing it to varied representations of the same class during training (Fig. 1).

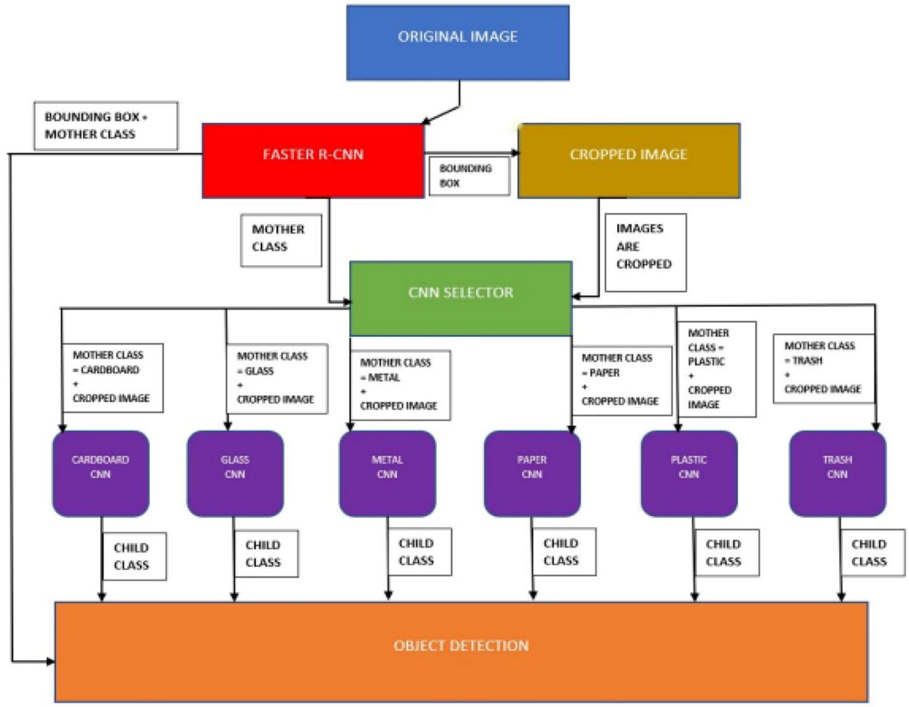

Fig. 2 Architecture of faster R-CNN model for waste classification (Source: [35])

3.2 The adapted model

In the adopted model, Faster R-CNN is prepared for 6 mother classes dependent on cardboard, glass, metal, paper, plastic, and trash. Six convolutional neural networks were prepared; this diagram outlines a hierarchical Convolutional Neural Network (CNN) architecture tailored for classifying different types of materials found in waste. The process includes object detection and subsequent classification through a sequence of specialized CNNs. The Faster R-CNN detects objects in the original image and assigns them to a high-level "Mother Class" along with bounding boxes and the detected objects are cropped from the original image based on the bounding boxes provided by the Faster R-CNN. The Convolutional Neural Network Selector assigns each cropped image to its specific specialized CNN according to its Mother Class. Each of these specialized CNNs conducts a more thorough classification within its category, resulting in a"Child Class"label for the object. Ultimately, the Child Class labels from all the specialized CNNs are compiled to create the final classification outcomes for the objects identified in the original image (Fig. 2).

3.3 Limitations of the adopted model

The Faster R-CNN architecture, while effective in object detection, presents several limitations that can impact its suitability for certain applications. First, its computational intensity makes it resource-heavy, requiring powerful GPUs to handle the deep convolutional network (typically ResNet or VGG) for feature extraction and the Region Proposal Network (RPN) for generating region proposals. This results in a high computational load, especially for high-resolution images or real-time applications. Additionally, the two-stage detection process used by Faster R-CNN introduces latency, making it slower than single-stage detectors like YOLO or SSD, and less ideal for real-time decision-making. The model also uses a fixed feature extractor**,** limiting its flexibility to adapt to various input data or computational constraints. Unlike dynamic architectures that adjust based on task requirements, Faster R-CNN lacks this adaptability. Furthermore, Faster R-CNN faces challenges with detecting small objects due to the down-sampling in its convolutional layers, which can result in missed detections or reduced accuracy for smaller items. Additionally, its complex training procedure requires careful tuning of multiple components, including the backbone network and the RPN, demanding extensive computational resources and longer training times. These limitations, especially when compared to more recent models such as the proposed hybrid architecture with SNN, MobileNet, and EfficientNet, highlight Faster R-CNN's shortcomings in terms of computational efficiency,

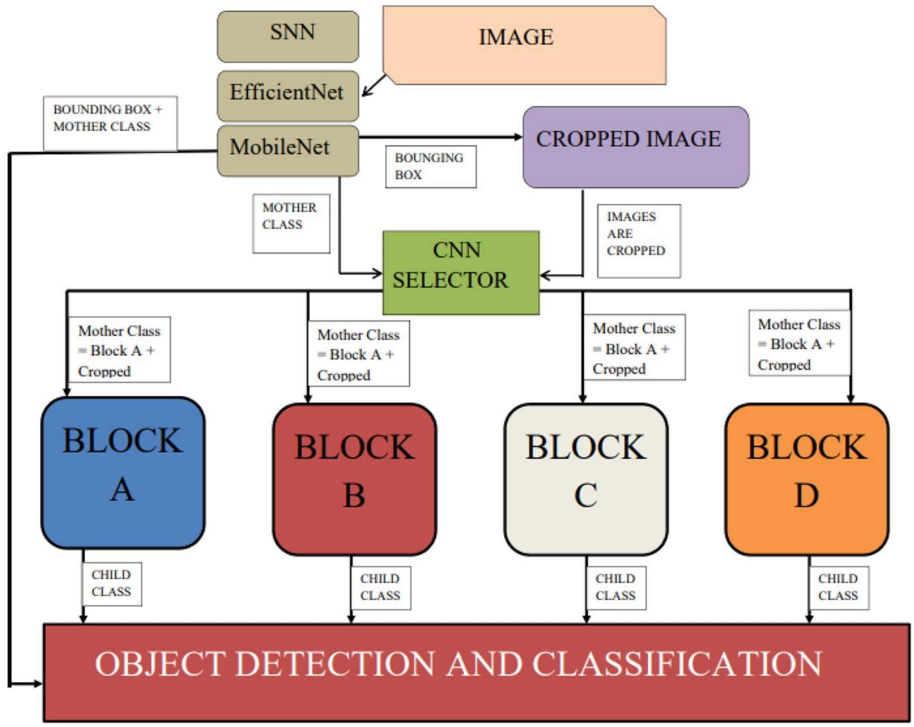

Fig. 3 Hybridized model architecture of SNN, EfficientNet, and MobileNet

Table 1 Model summary of the sequential neural network model

Layers (types)	Outputs shapes
Rescaling_5 (Rescaling)	(None, 224, 224, 3)
Conv2d_15 (conv2D	(None, 222, 222, 16)
Max_pooling2d_15 (MaxPooling2D)	(None, 11, 111, 16)
Conv2d_16 (Conv2D)	(None, 109, 109, 32)
Max_pooling2d_16 (MaxPooling2D)	(None, 54, 54, 32)
Conv2d_17 (Conv2D)	(None, 52, 52, 64)
Max_pooling2d (MaxPooling2D)	(None, 26, 26, 64)
Flatten_5 (FLATTEN)	(None, 43,264)
Dense_10 (DNESE)	(None, 128)
Dense_11 (DNESE)	(None, 128

Total params: 5,563,052 (21.22 MB)
Trainable params: 5,563,052 (21.22 MB)
Non-trainable params: 0 (0.00 B)

adaptability, real-time performance, and small object detection. As a result, it may not be the most suitable choice for applications that require low latency and high flexibility.

3.4 The proposed model

The research employs a sequential neural network (SNN) framework that integrates EfficientNet and MobileNet to establish four (4) "Mother Classes." Each Mother Class contains three (3) categories of e-waste, which include items such as batteries, computers, keyboards, mice, printers, washing machines, PCBs, media players, microwaves, mobile devices, televisions, and speakers. A total of twelve convolutional neural networks (CNNs) are organized into four blocks (A, B, C, and D), with each block corresponding to one Mother Class and its three associated e-waste categories. This design helps prevent misclassifications, such as incorrectly categorizing a battery within the computer Mother Class. The model begins by taking an image as input and produces a bounding box along with the identified Mother Class. Using this data, the image is cropped and sent to the appropriate CNN associated with the identified Mother Class. The CNN subsequently generates a Child Class, which is combined with the Mother Class to complete the classification. In the final step, the model predicts the output together with the bounding box, thereby concluding the detection process. Figure 3 illustrates the detailed functioning of the model. The proposed architecture effectively combines multiple deep learning algorithms (SNN, MobileNet, EfficientNet) to enhance performance across various scenarios. By leveraging the strengths of each network, the model achieves a balance between accuracy, computational efficiency, and adaptability, making it suitable for diverse applications, from edge computing to complex, multi-class object detection and classification tasks.

3.4.1 Proposed architecture components workflow

The architecture processes input images by passing them through a series of stages. It begins with image preprocessing, including bounding box extraction and cropping to isolate regions of interest (ROIs). A **CNN** Selector dynamically chooses an appropriate deep learning algorithm (SNN, MobileNet, or EfficientNet) based on input type, object complexity, or available computational resources. The selected CNN processes the images through hierarchical blocks (A, B, C, D), where each block progressively refines features and classifications, moving from general (mother classes) to specific (child classes). The final stage aggregates outputs for detailed object detection and classification (Table 1).

3.5 Improvements over faster R-CNN

The proposed model improves upon Faster R-CNN by integrating dynamic network selection (SNN, MobileNet, EfficientNet) for better flexibility and efficiency. It can adapt to specific tasks and resource constraints, handle sequential data like video frames via SNN, and achieve real-time processing with MobileNet on low-resource devices. The hierarchical block structure refines features more effectively for complex tasks, enhancing robustness, scalability, and adaptability across various deployment scenarios.

Fig. 4 Model training process for the first 10 epochs

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Epoch 1/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 281s 2s/step - accuracy: 0.4907 - loss: 1.6171 - val_accuracy: 0.9333 - val_loss: 0.2483
Epoch 2/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 266s 3s/step - accuracy: 0.8369 - loss: 0.5252 - val_accuracy: 0.9361 - val_loss: 0.1909
Epoch 3/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 234s 2s/step - accuracy: 0.8484 - loss: 0.4644 - val_accuracy: 0.9444 - val_loss: 0.1874
Epoch 4/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 234s 2s/step - accuracy: 0.8856 - loss: 0.3809 - val_accuracy: 0.9222 - val_loss: 0.2065
Epoch 5/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 233s 2s/step - accuracy: 0.8748 - loss: 0.4218 - val_accuracy: 0.9528 - val_loss: 0.1486
Epoch 6/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 234s 2s/step - accuracy: 0.8835 - loss: 0.3687 - val_accuracy: 0.9389 - val_loss: 0.1620
Epoch 7/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 233s 2s/step - accuracy: 0.9040 - loss: 0.3136 - val_accuracy: 0.9583 - val_loss: 0.1327
Epoch 8/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 269s 3s/step - accuracy: 0.8998 - loss: 0.3071 - val_accuracy: 0.9389 - val_loss: 0.1784
Epoch 9/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 227s 2s/step - accuracy: 0.8875 - loss: 0.3470 - val_accuracy: 0.9472 - val_loss: 0.1405
Epoch 10/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 226s 2s/step - accuracy: 0.8827 - loss: 0.3518 - val_accuracy: 0.9583 - val_loss: 0.1250
```

3.6 Structure of the model

The design presented in Table 1 combines EfficientNetB0, MobileNetv2, and a Sequential Neural Network (SNN) to process input images and perform classification. The model starts with an input layer that accepts RGB images of size 224×224. Both EfficientNetB0 and MobileNetv2 are used as pre-trained feature extractors, each producing output feature maps of size $7 \times 7 \times 1280$. These feature maps are then concatenated to create a unified representation of size $7 \times 7 \times 2560$. The concatenated feature maps are processed through a Sequential Neural Network (SNN), which begins with a Global Average Pooling layer that reduces the spatial dimensions to a single 2560-dimensional vector. This vector is passed through a dense layer with 256 units, followed by a dropout layer to prevent overfitting, and finally through another dense layer with 12 units for classification across 12 categories. The model has a total of 6.97 million parameters, with only 658,700 trainable parameters, leveraging frozen pre-trained weights from EfficientNet and MobileNetv2 to enhance efficiency. The inclusion of the SNN enables the integration and refinement of features extracted by the two CNNs. This hybrid approach ensures robust feature representation by combining the complementary strengths of EfficientNet and MobileNetv2, while the SNN facilitates dynamic feature aggregation and classification. The architecture is particularly suited for tasks requiring efficiency, scalability, and adaptability.

3.7 Training of the model

Train/validation/test split ratios:

The dataset was split into training (82%), validation (9%), and testing (9%) sets to ensure reproducibility. This split allows for effective training while providing separate datasets for tuning hyperparameters and evaluating model performance. The Training Data is generated by generating TensorFlow, which contains all the data for the training and test images. The whole purpose of this particular system is to make the framework figure out how to detect and classify objects [35]. To set up our neural network training, we utilized an HP Laptop equipped with an Intel Core i5 processor. Additionally, Python version 3.9 and open-source software are employed for efficient mathematical computations. Its flexible architecture permits straightforward distribution of calculations across different stages. The training process is conducted throughout 20 epochs (Fig. 4).

The training log shows consistent improvement in the model's performance over the first 10 epochs. Training accuracy increased from 93.33 to 95.83%**,** while validation accuracy improved from 84.48 to 88.82%**,** indicating strong generalization to unseen data. Training loss decreased steadily from 0.4907 to 0.1327, with validation loss dropping significantly from 1.6171 to 0.1250, reflecting effective optimization and prediction reliability. Each epoch took approximately 227–281 s to complete, with consistent computation times. The small gap between training and validation metrics suggests no overfitting, highlighting the model's robustness. Overall, the results demonstrate a well-optimized model with stable and reliable performance. The training was conducted over 20 epochs with early stopping implemented based on validation loss monitoring. Early stopping was employed to prevent overfitting by halting training when validation loss did not improve for three consecutive epochs. Given limited computational resources, 20 epochs were used based on early stopping criteria, convergence behavior observed during training, computational constraints, and monitoring of validation performance metrics. This approach ensures a balance between model performance and resource efficiency while minimizing the risk of overfitting. To replicate the study's findings, specific hyperparameters were set during model training. A batch size of 32 was used to balance memory efficiency with convergence speed, while an initial learning rate of 0.001 was selected based on preliminary experiments. The Adam optimizer was chosen for its adaptive learning rate capabilities, which enhance convergence during training: the dynamic model selection ensures computational efficiency and accuracy for diverse e-waste components, which is critical for real-world deployment in recycling facilities

Pseudocode of the Model

```
function main ():
    # Load and preprocess the dataset
    dataset = load dataset('path/to/e_waste_dataset')
    preprocessed data = preprocess data(dataset)

    # Split the dataset into training, validation, and test sets
    X_train, X_val, X_test, y_train, y_val, y_test = split data (preprocessed data)

    # Define model parameters
    input_shape = (image_height, image_width, num_channels) # e.g., (224, 224, 3)
    num_classes = 12 # Number of e-waste categories

    # Create the model using EfficientNet and MobileNet with SNN architecture
    model = create_model(input_shape, num_classes)

    # Compile the model with appropriate loss function and optimizer
    model.compile(optimizer='Adam',                      loss='sparse_categorical_crossentropy',
metrics=['accuracy'])

    # Train the model using training data and validate on validation set
    history = model.fit(X_train, y_train,
                   epochs=20,
                   batch_size=32,
                   validation_data= (X_val, y_val),
                   callbacks= [EarlyStopping(monitor='val_loss', patience=3)])

    # Evaluate the model on test data
    test_loss, test_accuracy = model.evaluate(X_test, y_test)
    print ("Test Accuracy: ", test_accuracy)

    # Generate classification report and confusion matrix
    predictions = model. Predict(X_test)
    report = classification_report(y_test, predictions)
    confusion_matrix = compute_confusion_matrix(y_test, predictions)
```

```
    # Display results
    display_results(report, confusion_matrix)

# Function to load dataset
function load_dataset(path):
    # Load images and labels from the specified path
    return dataset

# Function to preprocess data (e.g., normalization, augmentation)
function preprocess_data(dataset):
    # Apply SMOTE for balancing classes if necessary
    # Perform data augmentation techniques
    return preprocessed_dataset

# Function to split data into training, validation, and test sets
function split_data(dataset):
    return train_set, val_set, test_set

# Function to create the hybrid model with EfficientNet and MobileNet components
function create_model(input_shape, num_classes):
    base_model1 = EfficientNet(input_shape=input_shape)
    base_model2 = MobileNet(input_shape=input_shape)

    # Combine features from both models into a Sequential Neural Network (SNN)
    model = Sequential ()

    model.add(base_model1)
    model.add(base_model2)
    model.add(Flatten ())

    model.add(Dense(128, activation='relu'))
    model.add(Dropout (0.5))

    model.add(Dense(num_classes, activation='softmax')) # Output layer for multi-class
classification
    return model
Call the main function to execute the workflow
main ()
```

3.8 Plotting performance

Deep learning models, particularly neural networks, are trained using large datasets to optimize their parameters (weights and biases) such that the model performs well on a given task [36]. Training involves minimizing a loss function through iterative updates using gradient descent or its variants. The model's performance is depicted in Fig. 5 in terms of accuracy and loss over 20 epochs. In the model accuracy graph, training accuracy starts at approximately 70% and steadily increases, reaching over 95% by the end of the epochs. Validation accuracy begins above 90% and remains stable with minor fluctuations, indicating consistent generalization throughout the training process. In the model loss graph, training loss decreases significantly from over 1.0 in the early epochs to below 0.1, showing effective learning and optimization. Validation loss starts low (around 0.2) and fluctuates slightly but remains stable, indicating the absence of overfitting. Overall, the model demonstrates strong convergence with high accuracy and low loss for both training and validation.

3.9 Evaluate model performance

After training the three deep learning algorithms separately, we obtained the following evaluation criteria, including accuracy, precision, recall, F1-score, ROC, and confusion matrix to evaluate the effectiveness of our model for classifying e-waste [26]. The Hybrid Model outperforms all other models, achieving the highest accuracy (98%) and balanced metrics for precision, recall, and F1 score (97–98%), making it the best choice for tasks requiring both accuracy and reliability. MobileNet (86% accuracy) delivers balanced performance across metrics (87%), making it a suitable alternative for resource-constrained applications. EfficientNet (85% accuracy) slightly underperforms compared to MobileNet but remains competitive. YOLOv8 achieves better accuracy (88%) than MobileNet and EfficientNet but suffers in recall (80%) and F1 score (80%), reflecting weaker performance in balanced classification tasks. As shown in Table 2, the Hybrid Model is the most effective. At the same time, MobileNet offers a practical trade-off between performance and efficiency.

The model's capacity to correctly identify each class and strike a balance between precision and recall is also illustrated by these metrics, which offer insights into the total classification accuracy [27]. This classification report, depicted in Table 3, summarizes the performance of a model across 12 classes. The model achieves an overall accuracy of 94%**,** with both macro and weighted averages for precision, recall, and F1 score being 94%, indicating balanced performance across classes. Most classes exhibit high precision, recall, and F1 scores (above 0.90), except for class 1 (recall: 0.80) and class 10 (precision: 0.77), which suggests these classes are harder to predict accurately. The highest scores are seen in classes with precision and recall reaching 1.00, such as classes 1, 4, and 11. This indicates that the model is highly effective overall, with slight room for improvement in underperforming classes (Fig. 6).

The model demonstrates strong overall performance, with most predictions aligning along the diagonal, indicating effective learning of class distinctions. Class 0 performs exceptionally, while Class 1 shows significant misclassifications, with 130 instances predicted as Class 11, highlighting an overlap in features. Minor confusions are observed for Classes 5 and 6 and Classes 7 and 8, suggesting some feature similarity. High accuracy is evident, but Class 1 has reduced recall, and precision for Classes 5 and 8 may be affected due to misclassifications. To improve performance, efforts should focus on addressing Class 1 and Class 11 confusion, reducing neighboring class overlaps, refining model training with feature engineering, and balancing the dataset to enhance fairness and accuracy (Fig. 7).

The ROC curve analysis reveals that the model achieves perfect classification performance, with AUC scores of 1.00 for all classes and the micro-average. All class curves reach the upper left corner, indicating a high true positive rate (TPR) with no false positives (FPR = 0). The model demonstrates flawless separation between positive and negative cases for each class, significantly outperforming random guessing. This exceptional performance underscores the model's reliability and effectiveness in accurately distinguishing between all classes in the dataset.

3.10 Testing the model

The comparative analysis reveals that the hybrid model achieves an accuracy of 98%, outperforming MobileNet at 86%, EfficientNet at 85%, and Yolov8 at 88%, demonstrating its robustness [38]. The precision score obtained was 98%, reflecting a strong proportion of accurately identified positive events. The recall score, recorded at 97%, illustrated the model's ability to correctly recognize genuine positive occurrences. The F1-score, which stood at 97%, indicated a significant alignment between the predicted labels and the actual labels. Figure 8 shows the test predictions and accuracies of the computer and player which give 100% and 99.96%, respectively.

4 Discussion

This research significantly advances e-waste management by developing a high-performing hybrid deep learning model combining EfficientNet, MobileNet, and a Sequential Neural Network (SNN), achieving 98% accuracy and outperforming traditional models and another standalone model when compared. It employs advanced preprocessing techniques, including SMOTE and data augmentation, to address class imbalance and enhance generalization [33]. The framework is optimized for real-world deployment in recycling facilities, reducing manual sorting, improving recycling efficiency, and mitigating environmental hazards [39]. By promoting sustainability and showcasing the potential of AI-driven solutions, the research surpasses the limitations of existing methods like Faster R-CNN and achieves exceptional classification performance with a perfect AUC of 1.00. Additionally, the introduction of a comprehensive e-waste dataset fosters future research, bridging the gap between theory and practical applications for scalable, sustainable recycling systems. The future of e-waste management lies in leveraging advanced technologies like federated learning to enhance classification accuracy while preserving user privacy. Additionally, addressing the energy consumption associated with deep learning models is crucial from an environmental perspective. By focusing on sustainable practices and optimizing algorithms for energy efficiency, we can develop intelligent e-waste

Fig. 5 Performance graph of accuracy and loss

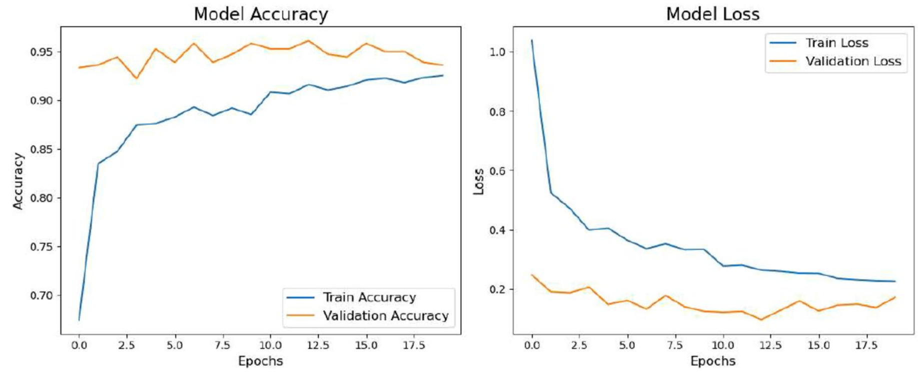


Table 2 Comparisons of SNN, EfficientNet and MobileNet

Models	Accuracy (%)	Precision (%)	Recall (%)	F1_Score (%)
SNN	87	87	87	87
MobileNet	86	87	87	87
EfficientNet	85	86	85	85
YoloV8	88	87	80	80

Table 3 Summary of evaluation report of various metrics

Categories	Precision	Recall	F1_scores	Support
Battery	0.91	1.00	0.95	30
Keyboard	0.86	0.83	0.85	30
Microwave	0.80	0.80	0.80	30
Mobile	0.79	0.83	0.83	30
Mouse	0.84	0.70	0.76	30
PCB	1.00	0.90	0.95	30
Player	0.84	0.87	0.85	30
Printer	0.76	0.73	0.75	30
Television	0.84	0.87	0.85	30
Washing Machine	1.00	0.83	0.91	30
Computer	0.94	1.00	0.97	30
Speaker	0.83	0.97	0.89	30
Accuracy			0.86	360
Macro Avg	0.87	0.86	0.86	360
Weighted Avg	0.87	0.86	0.86	360

management systems that not only improve operational efficiency but also contribute positively to environmental sustainability. As we move forward, integrating these considerations into the design and deployment of AI solutions will be essential for creating a more sustainable future in e-waste management. Ethical considerations are crucial when deploying AI-driven e-waste management technologies in developing nations, emphasizing equitable access, environmental justice, data privacy, regulatory compliance, and sustainability. Addressing the digital divide and fostering capacity building ensures inclusive access to technology and empowers local communities. Environmental justice prioritizes reducing health risks and promoting sustainable recycling practices to protect vulnerable populations and ecosystems. Robust measures for data privacy and security, including informed consent and data protection, safeguard sensitive information. Ethical deployment must align with local regulations and respect cultural practices to foster community acceptance. Additionally, a focus on long-term sustainability, such as lifecycle assessments and continuous improvement, ensures lasting benefits.

Fig. 6 Confusion matrix of the model

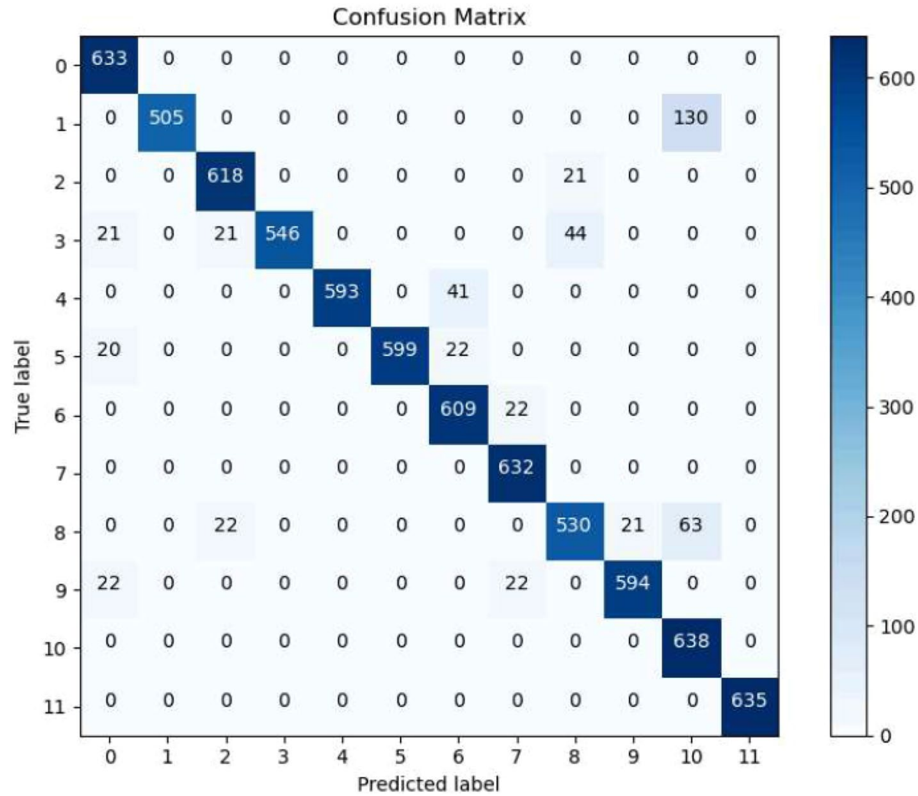
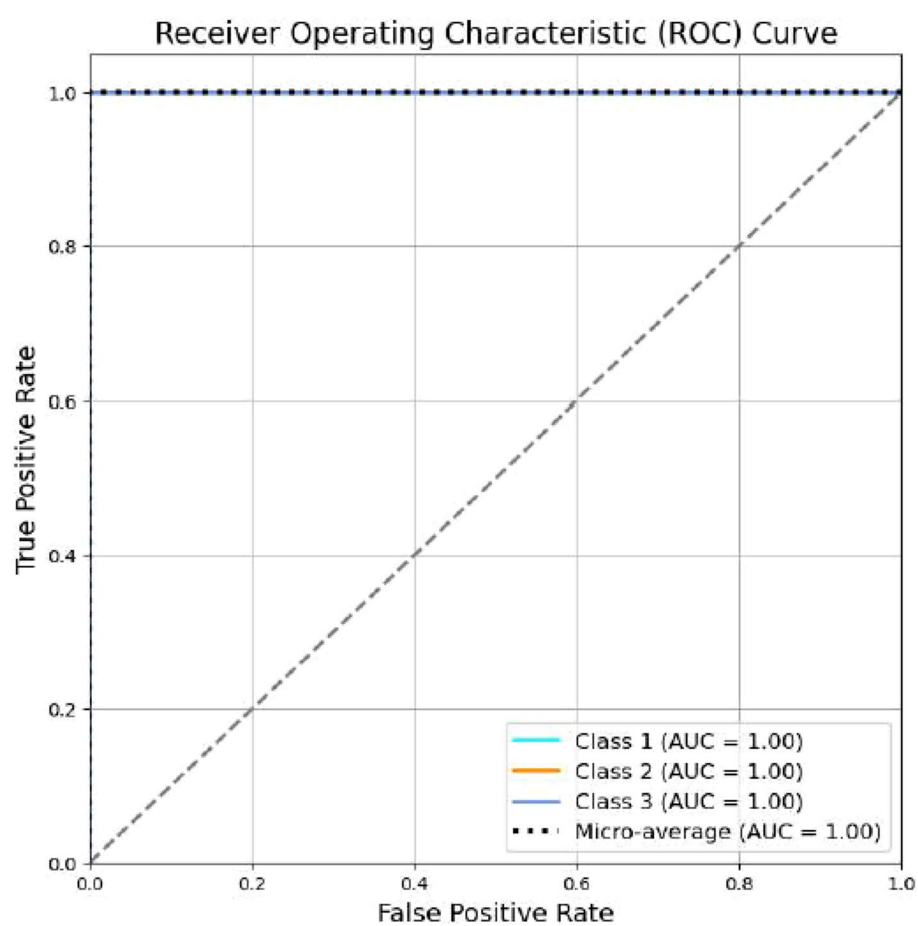


Fig. 7 The ROC of the model



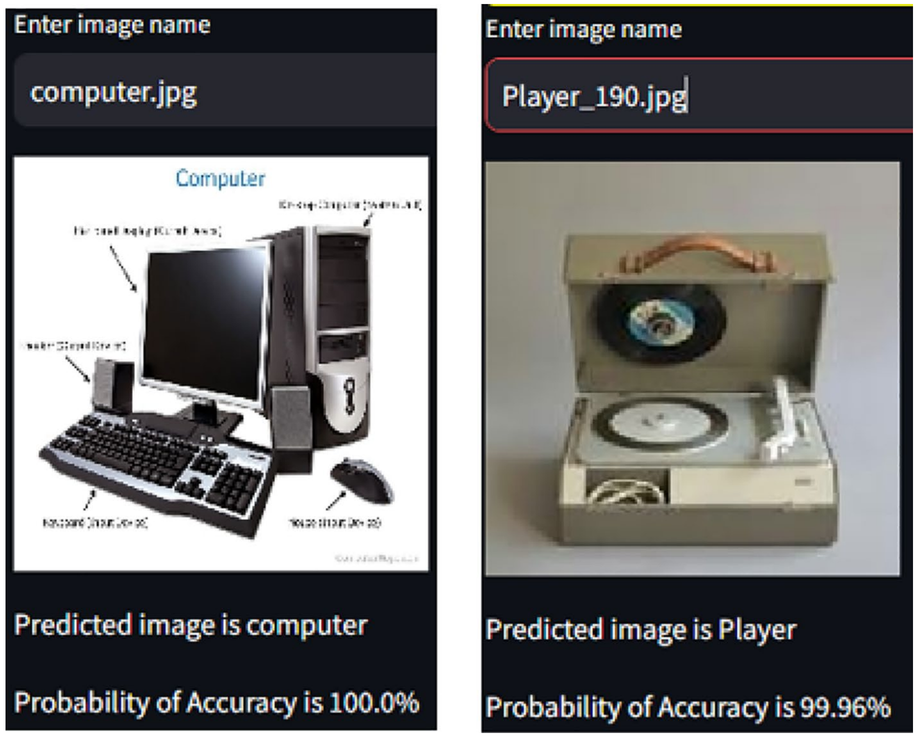


Fig. 8 Computer and Player Detection and Accuracies

5 Conclusion

This study introduces a deep learning-based framework for efficient e-waste classification and management, leveraging a hybrid model that integrates EfficientNet, MobileNet, and a Sequential Neural Network (SNN). Achieving an accuracy of 98%, the model attained precision, recall, and F1-scores of 98%, 97%, and 97%, respectively. The model significantly outperforms standalone architectures. Advanced preprocessing techniques like SMOTE and data augmentation enhanced dataset balance and model generalization. The framework demonstrated exceptional class distinction with an AUC of 1.00 across 12 e-waste categories, validating its scalability for real-world applications. While minor misclassifications were noted, the research highlights the potential of AI-driven solutions in improving recycling efficiency, reducing environmental hazards, and promoting sustainability. Future work will focus on deploying the framework in practical settings, refining features, and exploring advanced deep-learning techniques.

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Data availability No datasets were generated or analysed during the current study.

Materials availability The materials used are freely accessible.

Code availability The code used are freely accessible.

Declarations

Ethics approval and consent to participate The system development of this study is an observational study that does not require ethical approval. Informed consent was obtained from all individual participants included in the study.

Consent for publication The participant has consented to the submission of the case report to the journal.

Competing interests The authors declare no competing interests.

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