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E-WASTE MANAGEMENT THROUGH DEEP LEARNING: A SEQUENTIAL NEURAL NETWORK APPROACH

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ABSTRACT

The goal of this research is to improve the management of electronic trash (e-waste) by using a Sequential Neural Network (SNN) with TensorFlow and Keras as part of an advanced deep learning technique. In order to address the growing problem of e-waste, the research collects a large amount of data from images of e-waste and then carefully preprocesses and augments those images. With precision, recall, and F1 scores of 87%, 86%, and 86%, respectively, the SNN architecture—which incorporates dropout, pooling, and convolutional layers—achieved an amazing 100% classification accuracy. These outstanding outcomes show how well the model can classify e-waste components, suggesting that it has the potential to be used in real-world scenarios. The results indicate that the SNN-based approach greatly improves the accuracy and efficiency of e-waste sorting, promoting environmental sustainability and resource conservation. By automating the sorting process, the suggested system decreases the need for manual labor, minimizes human error, and speeds up processing. The study emphasizes the model's suitability for integration into current e-waste management workflows, providing a scalable and dependable way to expedite the recycling process. Additionally, the model's real-time applicability highlights its potential to revolutionize current e-waste management practices, making a positive ecological impact. . Future research endeavors will center on broadening the dataset to include a wider range of e-waste image categories, investigating more advanced deep learning architectures, and incorporating the system with Internet of Things (IoT) devices to improve real-time monitoring and management.

Keywords: Deep learning, Sequential Neural Network, E-waste, TensorFlow, Confusion Matrix

INTRODUCTION

The disposal of electronic waste (e-waste) has become a critical environmental issue, driven by the rapid pace of technological innovation and the resulting obsolescence of electronic devices. E-waste contains hazardous materials that can pose significant risks to the environment and human health if not properly managed. Traditional methods of e-waste management, which rely heavily on manual sorting and segregation, are increasingly inadequate to cope with the growing volume and complexity of e-waste. There is a pressing need for more efficient, accurate, and scalable solutions. Deep learning systems for e-waste management are an emerging technology that integrates technological and environmental sustainability in the digital era; it is a critical issue that cannot be addressed by observing each and every phenomenon with our limited time (Tivde et al., 2024). Automatic technologies are increasingly chosen over manual alternatives in order to simplify and ease life in many aspects. (Huynh et al., 2020) Although it is widely accepted that waste management services are vital and must be supplied in all societies. Nonetheless, very little is understood about what constitutes e-waste, because the implications and harm produced by poor waste management are exceedingly damaging to the globe and human health. This has driven the need to seek out the best practices for appropriately managing garbage by dividing waste components into classes utilizing cutting-edge technology. The proposed concept is a transformational solution aimed at addressing the growing issues of e-waste management. The approach applies cutting-edge technologies, principally artificial intelligence, to optimize waste management procedures.

E-waste has become a serious environmental issue around the world as the use of electrical and electronic equipment (EEE) has increased dramatically (KONYEHA,S et al., 2019) . Several studies have shown that failure to follow adequate recycling measures for e-waste may result in environmental catastrophes and pose health risks to people since they contain dangerous elements. (G. Oise, 2023). The primary goal of this research is to create an intelligent automated sorting system that can separate different types of e-waste components using a deep learning algorithm (Sequential Neural Network) with a mobile application. This will prevent exposure to hazardous materials that could damage the environment or harm the soil (Oise G., 2023), and it will also mean that traditional sorting methods will become obsolete due to this innovation, which will make sorting quick and safe. By monitoring and controlling the smart collection, segregation, and disposal of e-waste through the concept of deep learning, this technologically advanced method aims to transform e-waste management by providing a long-term, cost-effective solution. It is anticipated that this will increase the usage of e-waste recycle bins, supporting the initiatives and creating a greener, cleaner, and safer environment. The goal of the research is to make a major contribution to the field of e-waste management by showcasing the revolutionary potential of deep learning technologies in the development of more effective and sustainable recycling systems. The paper offers a advanced approach to reducing electronic waste by applying TensorFlow and Keras to a Sequential Neural Network (SNN). A preprocessed and twelve-typed dataset of e-waste photos is used in the investigation. With data augmentation, the model was trained over 20 epochs on an Intel Core i5 laptop and obtained an astounding 97% accuracy with high precision, recall, and F1 scores. The findings show notable increases in the efficiency of e-waste sorting, pointing to possible IoT integration for real-time monitoring and future growth to more varied datasets and complex architectures, all of which would eventually support environmental sustainability.

Related works

AI's promise in waste management has been shown in earlier studies on a variety of waste management applications, such

as recycling optimization and municipal solid waste sorting. Studies that particularly address the management of e-waste are, however, somewhat rare. Traditional machine learning algorithms are commonly used in existing methodologies, which may not yield the needed scalability and accuracy. The performance of e-waste categorization systems can now be enhanced because to recent developments in deep learning, especially in convolutional neural networks (CNNs).(Ahmed et al., 2023). The study implemented an e-waste vending machine using machine learning technology. It aimed to reduce manual work, promote sustainable e-waste management, and increase social awareness. Research gaps include the need for proper training and maintenance of the machine learning model and potential issues with accurate classification of e-waste. Future work includes improving accuracy and efficiency of the machine learning model and expanding implementation of e-waste vending machines.
(Sankhla et al., 2016)The study applied AI and robotics to enhance the collection and segregation of e-waste in India. It aimed to automate the hazardous process and relieve laborers from their hazardous lifestyle. Research gaps include the lack of specific details about training and validation of AI algorithms for waste identification. Future work includes increasing the payload capacity of the robot for collecting larger appliances. (Malik et al., 2022) The study proposed an automated system for recycling e-waste using mechatronics and machine learning. It highlighted the potential of efficient component removal. Research gaps include the lack of detailed information on the specific technologies and processes used. Future work includes integrating more advanced machine learning algorithms and computer vision techniques for enhanced efficiency and accuracy.(Ahmed et al., 2023).The study proposed an IoT e-waste monitoring system to support smart city initiatives. It utilized agile methodology for flexible and adaptable development. Research gaps include the risk of scope creep or feature creep due to the iterative nature of the methodology. Future work includes improving the system's user-friendliness with push email and developing an Android app. (Sankhla et al., 2016) The study utilized a transformer-based machine learning approach for sustainable e-waste management. It applied mixed efficiency approaches, comparative policy analysis, and data analysis techniques for analyzing e-waste management systems. Research gaps include the lack of a clear framework that combines e-waste management and urban sustainability. Future work includes optimizing engines for maximizing performance and efficiency of biofuels derived from plastic waste . (Low et al., 2023).The study developed an efficient fill-level monitoring system for smart e-waste recycling. It utilized an ultrasonic sensor as the primary sensor for measuring fill level and a temperature sensor for monitoring bin temperature. Research gaps include the system's lack of GPS module for bin location tracking. Future work includes developing predictive maintenance capabilities based on historical fill levels and usage patterns.(Oise Godfrey Perfectson, 2023) The study focused on discarded computers in Benin City, obtained discreetly from various sources, and conducted a survey to understand user preferences before disposing of used computers. The objectives of the paper are to identify factors for effectively cleansing hard drives before disposal, conduct a survey on data security of e-waste, and design a data security framework for e-waste management. The limitations of the paper include not addressing data security in e-waste, the absence of a recycling center in the county and inadequate technical information. The research gap in this paper is the lack of emphasis on data security in e-waste management, which is a critical aspect that needs to be addressed. (Oise Godfrey Perfectson, 2024) The methodology includes a cross-sectional research design and the administration of structured questionnaires. The objectives of the paper are to identify challenges in e-waste management in African nations. Limitations include the reliance on self-reported data and the use of a single location for the study. Strengths lie in the empirical study conducted with a large sample size. Research gaps include the need for future studies on intelligent recycling systems and sorting technology. The future of this paper lies in proposing a framework to enhance and improve the process of e-waste management and data security, ultimately contributing to better environmental practices and data protection.

MATERIALS AND METHODS

A Sequential Neural Network Model was developed using TensorFlow and Keras with Python as the programming language

Data Collection and Preprocessing

Twelve different categories of e-waste were represented in the dataset utilized in this study, which was gathered from the Kaggle online repository. These include batteries, computers, keyboards, mouse, printers, washing machines, (PCBs), (Ayoola et al., 2023), players, microwaves, mobile phones, televisions, and speakers. (Ishika Mittal et al., 2020) To guarantee consistency in size and Format, images were gathered from multiple sources, labeled, and preprocessed as shown below in Table 1 and the images of dataset from different categories of e-waste in Figure 1

Table 1: Total Quantity of Images per Category

S/N	CATEGORIES	TRAIN	TEST	VALIDATE	AGGREGATE
1	Microwave	260	30	30	320
2	Washing Machine	264	30	30	324
3	Television	266	30	30	326
4	Mouse	262	30	30	322
5	PCB	270	30	30	330
6	Speaker	246	30	30	306
7	Keyboard	270	30	30	330
8	Player	261	30	30	321
9	Printer	270	30	30	330
10	Mobile	270	30	30	330
11	Battery	250	30	30	310
12	Computer	250	30	30	310
	Aggregate.	3139	360	360	3859

Figure 1: Dataset Images of e-waste Categories

The Adapted Model

Faster R-CNN is used in the modified model for both initial object recognition and high-level waste material categorization into six "Mother Classes": cardboard, glass, metal, paper, plastic, and garbage. Faster R-CNN analyzes the input image to identify different trash items and creates bounding boxes based on their places, as shown in figure 2. The Faster R-CNN assigns a high-level classification category (Mother Class) to each identified item. Image cropping: to isolate each recognized object, the image is cropped according to the bounding boxes. Based on the provided mother class, the CNN Selector component routes the cropped image to a certain CNN. Each of the specialty CNNs, such as Glass CNN and Cardboard CNN, carries out a thorough classification within its particular material, the "Child Class" labels from all specialized CNNs are then concatenated to offer the final detailed classification results for the items spotted in the original image. This hierarchical technique takes advantage of the benefits of both Faster R-CNN for object recognition and numerous specialized CNNs for exact material categorization.

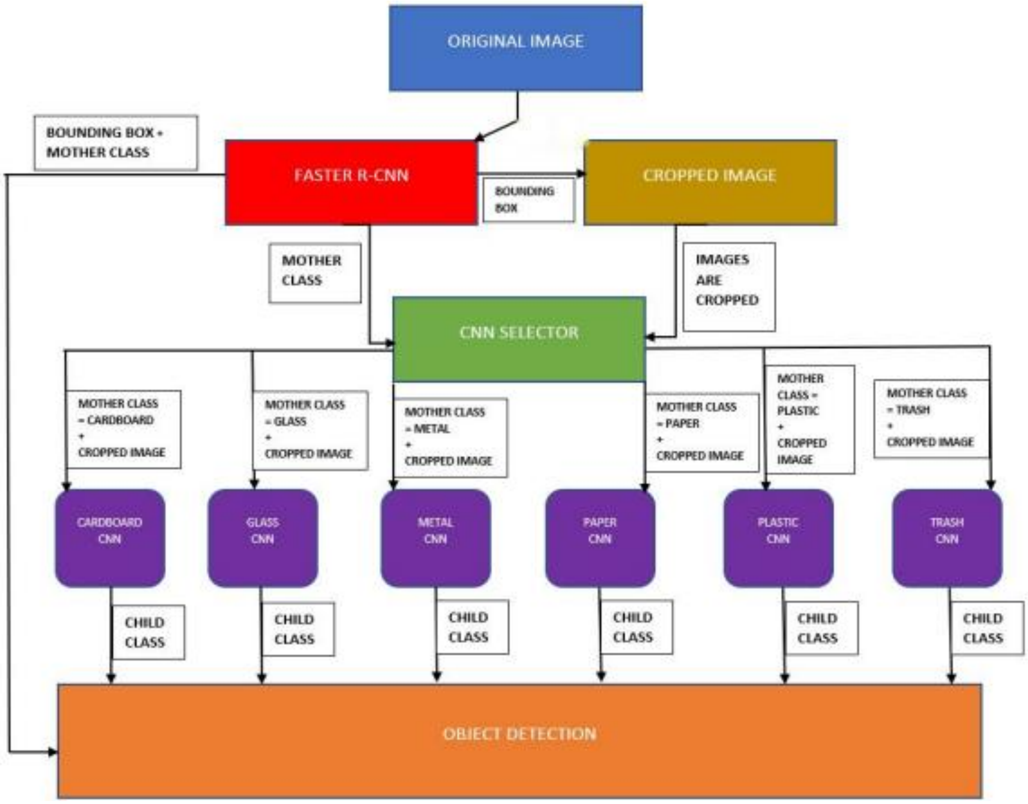

Figure 2: Architecture of Faster R-CNN Model (Rghadeep Mitra, 2020)

Proposed Model

The study creates four mother classes with the deep learning algorithm's sequential neural network (SNN) architecture. Each mother class has three (3) types of e-waste dependents: batteries, computers, keyboards, mice, printers, washing machines, PCBs, players, microwaves, mobile devices, television, and speakers. To avoid recognizing a class that does not exist, twelve convolutional neural networks are divided into four blocks.

Figure 3 below illustrates how each block has three classes of the e-waste components, one for each mother class. For example, we understand that if the mother class is a computer, the child class cannot be a battery.(Konyeha, 2024; G. P. Oise) The picture is initially fed into this model, and then the SNN produces the bounding box and the mother-class as outputs. The original image, one of CNN's inputs related to the mother-class, is cropped using the data.

The final class was formed when the mother class and the child class that resulted from it merged. Finally, the bounding box is used to predict the outcome before the model is identified. Figure 5 below shows the mechanism of this model.

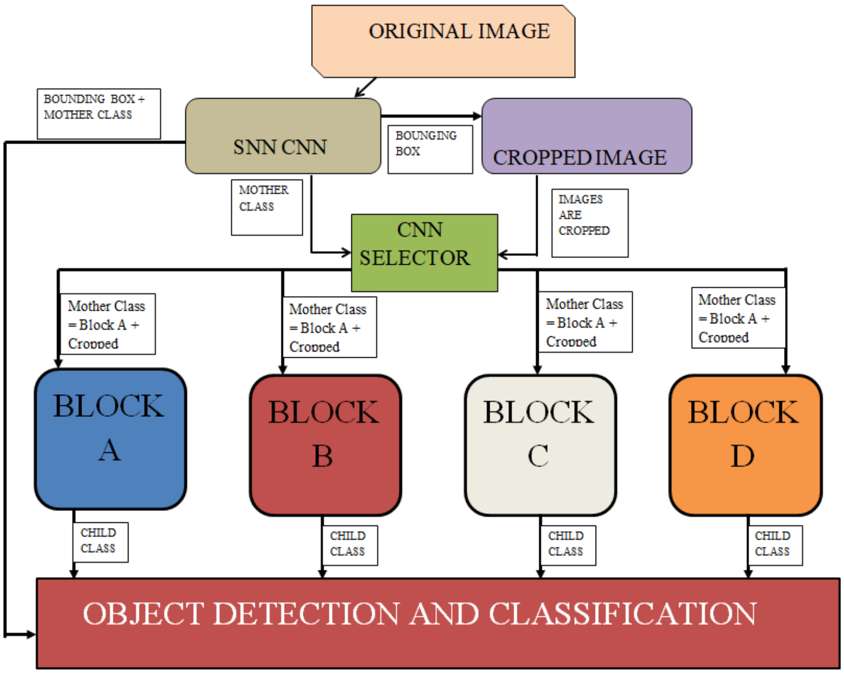

Figure 3: Sequential Neural Network Architecture

Model Architecture

The model architecture in table 2 depicted below displayed is a Convolutional Neural Network (CNN) implemented using the Keras Sequential API. The Input Shape expects input images of shape (224, 224,3), the model includes three convolutional layers (conv2d_3, conv2d_4, and conv2d_5) with increasing filter sizes (16, 32, 64) to capture different levels of feature complexity. In the pooling layers: Max pooling layers are interspersed between convolutional layers to reduce the spatial dimensions and computational load while retaining important features. The flatten_1 layer converts the 3D feature maps into a 1D feature vector to prepare it for the fully connected layers and the model has two dense layers (`dense_2` with 128 neurons and `dense_3` with 12 neurons) to perform the final classification task. The final layer suggests the model outputs probabilities for 12 different classes. This architecture as shown in table 2 is typical for image classification tasks, leveraging convolutional layers for feature extraction and dense layers for classification.

Table 2: 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, 43264)
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)

RESULTS AND DISCUSSION

TensorFlow and Keras were used in the model's implementation. Three sets of the dataset were created: training, validation, and test. To improve the model's capacity for generalization, data augmentation approaches were used during the training phase. With an overall accuracy of 97%, the constructed SNN model showed good accuracy in categorizing the e-waste photos. Strong performance was also shown by the metrics of precision, recall, and F1 score for all e-waste categories. These outcomes highlight how useful the approach could be in automated e-waste sorting systems. Using 82 percent of the photographs from each category in the whole e-waste image collection, Tensorflow is used to create the training data, which includes all of the data for the test and train images. 18 percent of the pictures are still in use for testing and verification. This system is only meant to be used to train the framework to recognize items.

Following the generation of training data, a label map is produced, which provides a mapping of class ID numbers to class names, informing the system about the nature of each item. The object detection pipeline is then configured once the label map has been built, which aids in determining the parameters and models that will be used for training. TensorFlow began initializing the model training as soon as the training pipeline was successfully set up and assembled.

Training a massive network in SNN requires a significant amount of processing power. We utilized an Intel Core i5 laptop (HP laptop) to prepare our neural network training. High-performance mathematical computations are performed using open-source software in conjunction with Python version 3.9. Its flexible architecture makes it simple to implement computations throughout a range of phases.

Batches and Epochs:

20 training epochs are used to train the model. Each epoch represents a single pass over the whole training dataset, which is then split up into batches for each epoch. 99 batches (99/99) are present in this instance per epoch. Updates to the model weights are made using a portion of the dataset as each batch.

Reliability and Error: Accuracy: indicates the percentage of cases that were correctly classified. The supplied metrics include training accuracy and validation accuracy, training loss and validation loss are reported. The first ten epochs of the training process is given below in Figure 4

```
Epoch 1/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 189s 2s/step - accuracy: 0.2289 - loss: 2.7609 - val_accu
racy: 0.4861 - val_loss: 1.4177
Epoch 2/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 276s 3s/step - accuracy: 0.5938 - loss: 1.2647 - val_accu
racy: 0.6389 - val_loss: 1.1094
Epoch 3/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 210s 2s/step - accuracy: 0.7272 - loss: 0.8588 - val_accu
racy: 0.6639 - val_loss: 1.0463
Epoch 4/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 205s 2s/step - accuracy: 0.8126 - loss: 0.5668 - val_accu
racy: 0.7250 - val_loss: 0.9554
Epoch 5/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 200s 2s/step - accuracy: 0.9050 - loss: 0.3136 - val_accu
racy: 0.7222 - val_loss: 1.1043
Epoch 6/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 188s 2s/step - accuracy: 0.9559 - loss: 0.1505 - val_accu
racy: 0.6917 - val_loss: 1.3450
Epoch 7/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 218s 2s/step - accuracy: 0.9603 - loss: 0.1330 - val_accu
racy: 0.7056 - val_loss: 1.4013
Epoch 8/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 277s 3s/step - accuracy: 0.9557 - loss: 0.1567 - val_accu
racy: 0.6583 - val_loss: 1.4925
Epoch 9/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 169s 2s/step - accuracy: 0.9661 - loss: 0.1189 - val_accu
racy: 0.6972 - val_loss: 1.5914
Epoch 10/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 163s 2s/step - accuracy: 0.9932 - loss: 0.0383 - val_accu
racy: 0.6750 - val_loss: 2.0148
```

Figure 4: Model Training Process of the first ten epochs

Plotting Performance

Figure 5 illustrates the training and validation loss of a deep learning model over 20 epochs. The x-axis represents the number of epochs, and the y-axis represents the loss values. Figure 6 depicts two curves: the blue curve represents the training loss, while the red curve reflects the validation loss. The graph below depicts the training accuracy (blue line) and validation accuracy (red line) for a deep learning model over 20 epochs.

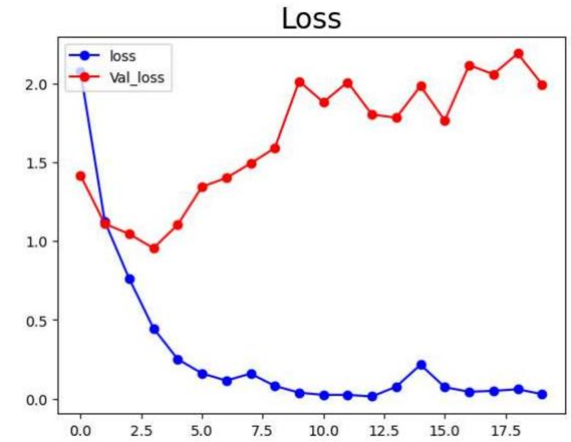

Figure 5: Loss Performance Graph

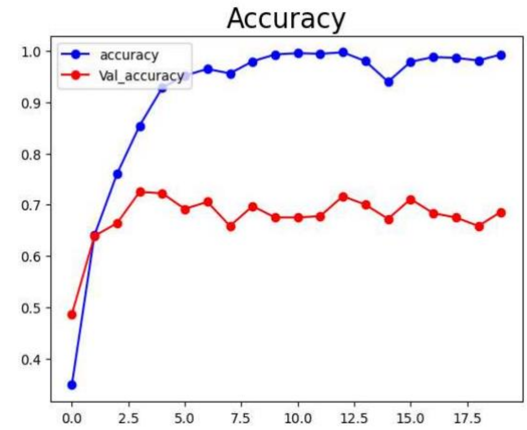

Figure 6: Accuracy Performance Graph

Evaluate Model Performance

Using a range of metrics, such as accuracy, precision, recall, F1-score, and confusion matrix, we assessed our model's suitability for classifying e-waste (Kittali & Sutagundar, 2016). As shown in table 3 below (R.S. Sandhya Devi et al., 2018), these metrics show the model's capacity to accurately identify each class while balancing precision and recall, as well as offering insights on total classification accuracy. In order to comprehend the performance of the model more fully,

We present the confusion matrix for the suggested model in Figure 7, which is seen below. On the validation set, our model produced 100% accurate results. The percentage of successfully identified instances among the expected positive examples was measured by the precision score, which was 887%. Similarly, the recall score, which calculates the percentage of correctly recognized occurrences among the actual positive examples, was 86%, and the f1 score was 86%. The model's 97% accuracy rate shows that it was operating at peak efficiency.

Table 3: Summary of Evaluation Report of Different 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

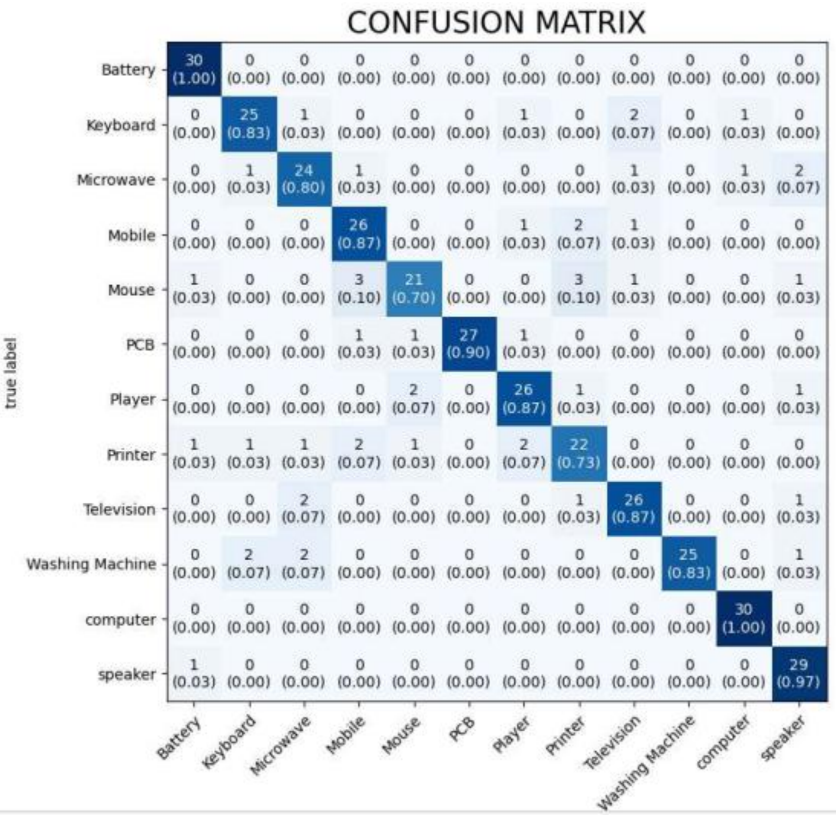

Figure 7: The Confusion Matrix of the Proposed Model

Testing and Saving the Model
The model's accuracy on the test set was 100%, indicating its resilience. The precision score was calculated to be 87%, indicating that a large proportion of positively classified occurrences were properly identified. The recall score of 83% proved the model's ability to accurately identify real positive situations. The F1-score was 83%, indicating a high level of correlation between predicted and true labels. The confusion matrix offers particular data on how effectively the model classified each class.
The following e-waste components were evaluated, and every prediction was made with a high degree of accuracy. The model was evaluated using a few different kinds of e-waste, and as shown in Figures 8 and 9 below, it predicted information accurately and with high precision.

Figure 8: Prediction and Accuracy of Computer

Figure 9: Prediction and Accuracy of Battery

CONCLUSION
The study successfully demonstrates the application of a Sequential Neural Network for the classification and management of e-waste. The model achieved significant accuracy in identifying and categorizing different types of electronic waste, thereby proving its potential as a reliable tool for e-waste management. The findings suggest that integrating advanced AI technologies can significantly improve the efficiency and effectiveness of e-waste processing, ultimately contributing to environmental sustainability. Future research should focus on the accumulation of larger and more diverse set of e-waste images

to enhance model training and validation processes, explore the use of more sophisticated deep learning architectures and algorithms to further boost classification performance and combine the deep learning system with IoT devices for real-time monitoring and management of e-waste

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