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Research Article

A Deep Learning Approach to Efficient E-Waste Management and Environmental Sustainability

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Abstract

Electronic waste (e-waste) poses significant environmental and health risks due to improper disposal and recycling methods. This research addresses these challenges by developing an intelligent, automated sorting system using a deep learning algorithm, specifically a Sequential Neural Network (SNN) implemented with TensorFlow and Keras. The system is designed to classify various e-waste components, such as circuit boards, batteries, and mobile devices, based on a comprehensive dataset comprising over 3000 e-waste images. The proposed SNN architecture integrates convolutional layers for feature extraction, followed by pooling and dropout layers, leading to fully connected layers and a softmax output for multi-class classification. The research details the design and implementation phases of the SNN, emphasizing its potential to significantly improve the efficiency of e-waste sorting and promote environmental sustainability. Key performance metrics include an overall accuracy of 87%, precision of 87%, recall of 86%, and an F1-score of 86%. These results highlight the model's effectiveness in accurately classifying e-waste categories. This technologically advanced approach aims to revolutionize e-waste management by providing a long-term, cost-effective solution. By facilitating intelligent collection, segregation, and disposal of e-waste, the system fosters a cleaner, safer, and greener environment. The research underscores the importance of integrating advanced machine learning techniques into waste management practices to address pressing environmental issues and promote sustainable development.

Keywords: Automated System, Hazardous, Deep Learning, E-waste, Environmental Health

1. Introduction

An emerging technology that integrates environmental and technological sustainability in the digital age is the deep learning system for managing e-waste [1]. This is an important issue that cannot be handled by observing every little thing on our hectic schedules. Nowadays, people choose automatic systems over manual ones in an effort to simplify and ease life in all respects [2]. Even so, it is widely acknowledged that waste management services are necessities that every community needs to offer. The consequences and harm caused by inadequate waste management are extremely dangerous to the world and human health, which has served as a wake-up call to the need to investigate the satiation before it causes even more harm to the world at large. Nevertheless, very little is known about what constitutes e-waste. This has made it necessary to search for the best method to use in order to manage the waste appropriately by classifying the waste components using the newest technological advancements. The idea as it is currently presented is a revolutionary way to deal with the growing difficulties associated with managing e-waste. The concept integrates cutting-edge technologies, primarily artificial intelligent to optimized 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 the improper recycling methods for e-waste can result in hazardous materials being present, which can pose health risks to humans and cause environmental catastrophes [2]. This research focuses on the development of an intelligent automated sorting system that uses a deep learning algorithm (Sequential Neural Network) with Tensorefow and Keras with a mobile application to separate different e-waste components [3]. This will prevent exposure to hazardous substances that damage the environment and soil, and it will make sorting obsolete because of its innovation, which will make sorting quick and safe. This technologically advanced approach aims to revolutionize e-waste management by providing a long-term, affordable solution [4]. 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). The environmental threat posed by the growing amount of electronic waste, or "e-waste," is exacerbated by the shortcomings of conventional manual sorting techniques. In order to increase the precision and effectiveness of e-waste management, this work presents a novel deep learning system for automated e-waste classification using a Sequential Neural Network (SNN) framework with TensorFlow and Keras [5]. The SNN was trained using a large dataset of more than 3000 e-waste photos, which included circuit boards, batteries, and mobile devices. 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. With precision and recall scores of 87% and 86%, respectively, and an F1 score of 86%, the model's astounding classification accuracy of 100% was attained by employing the sparse categorical cross-entropy loss function in conjunction with the Adam optimizer. 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.

Deep Learning, a subset of Artificial Intelligence, has revolutionized numerous fields with its advanced capabilities. It plays a critical role in various applications, including image recognition, speech-to-text conversion, speech and visual object recognition, drug discovery; face detection and recognition, and weather forecasting. The advent of High-Performance Computing (HPC) and advanced techniques like Big Data have significantly enhanced the processing of large datasets, leading to more accurate predictive outcomes through effective recognition [6]. Deep Learning employs computational models to process multiple layers, enabling the learning of data representations with various levels of abstraction. Convolutional Neural Networks (CNNs) have emerged as the most effective method for image classification in recent years. Unlike traditional methods that rely on handcrafted features extracted from segmented objects, CNNs automatically learn to identify features during the training process [7]. However, this training can be time-consuming.

1.1. Related Works

The study reviewed existing literature on the impact of electronic waste on environmental and human health [5]. It emphasized the need for proper e-waste management and suggested possible solutions and strategies. Research gaps include the lack of original research or data. Future work includes advocating for more efficient and sustainable e-waste management practices [8]. The study proposed an automated waste segregation system using sensors and a PLC-based system. It highlighted advantages such as modular design, flexibility, cost-effectiveness, and less wiring. Research gaps include the lack of experimental validation or real-world implementation of the proposed system. Future work includes implementing a robotic arm and PLC interconnected with sensors for material detection and addressing sensors' placement [9]. The study presented an IoT-based waste management system monitored by the cloud. It utilized smart waste bins with ultrasonic-level and gas sensors, cloud technology, and a mobile app for monitoring and conveying information. Research gaps include the lack of details on the methodology and validation of the system, and the case study was limited to a specific city. Future work includes using special cameras for waste recognition and implementing appropriate decisions [9]. The study developed a smart, automated waste management system using a modified form of the waterfall and prototyping methodology. It implemented features such as lid opening and closing, SMS alerts for the disposal truck driver, and demonstrated practical application. Research gaps include the lack of detailed discussion on scalability and adaptability to different waste management scenarios. Future work includes integrating advanced technologies like machine learning algorithms for predictive waste collection and optimization [10]. The study developed smart electronic waste collection systems using IoT technology. It utilized smart collection boxes, a backend server, and a mobile application for data recording and notifications. Research gaps include potential unreliability of the ultrasonic sensor used for level measurement and the use of low-cost sensors resulting in false readings. Future work includes implementing mobile applications, data collection systems, and IoT frameworks to enhance the system's capabilities [11]. The study focused on automatic waste segregation and management using a microcontroller and various sensors. It highlighted the use of different sensors for accurate detection and sorting of waste. Research gaps include the system's limitation to segregate waste into wet, metal, and dry categories and not handling more specific waste categories or hazardous waste. Future work includes implementing robots equipped with AI for efficient sorting [12]. The study proposed using thermal pyrolysis and catalytic pyrolysis to extract bio-oil from waste plastic. It discussed the cost-effectiveness of using bio-oil to minimize reliance on hydrocarbons and address environmental issues. Research gaps include the lack of mention of collecting plastic from e-waste or other sources. Future work includes designing the pyrolysis reactor for mixed waste plastics and small to medium-scale development [13]. 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 [9]. The study proposed an IoT-based waste monitoring and collecting system for a smart city. It utilized sensor units, a microcontroller, and a GSM module for IoT-based waste monitoring and communication. Research gaps include the time required for GPS module initialization, fluctuation in GPS data, and occasional poor network connectivity affecting message transmission. Future work includes implementing a real-time clock with a timestamp, developing an Android app with a locator, and integrating a grinder with the wet waste bin [12]. The study proposed an IoT-based e-waste management system that involves an android mobile application, e-waste bins or trucks locator, and a pay-as-you-throw system. It incentivizes proper disposal of electronic waste. Research gaps include the lack of discussion on the cost and scalability of implementing the proposed system and the feasibility and effectiveness in real-world scenarios. Future work includes developing machine learning algorithms for waste prediction and implementing blockchain technology for secure transactions.

This research aims to address these challenges by developing an intelligent, automated sorting system utilizing a deep learning algorithm, specifically a Sequential Neural Network (SNN) implemented with TensorFlow and Keras. The system is designed to classify various e-waste components, including circuit boards, batteries, and mobile devices, based on a comprehensive dataset of over 3000 e-waste images. The proposed SNN architecture integrates convolutional layers for feature extraction, followed by pooling and dropout layers, leading to fully connected layers and a softmax output for multi-class classification. The research outlines the design and implementation phases of the SNN, highlighting its potential to significantly enhance the efficiency of e-waste sorting and promote environmental sustainability. These results demonstrate the model's effectiveness in accurately classifying e-waste categories; this technologically advanced approach aims to revolutionize e-waste management by providing a long-term, affordable solution, fostering a cleaner, safer, and greener environment through intelligent collection, segregation, and disposal of e-waste.

2. Research Methodology

Research methodology is the process that demonstrates how a project is carried out with a clear outline of the methods to be used. Its shows how the research goal would be realized through the systematic execution of the objectives [14].

2.1 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 [15]. The dataset used for this research was collected from kaggle online dataset repository. The training data was obtainable which was mainly used in the classification of e-waste for recyclability status, which was classified as battery, computer, keyboard, mouse, printer, washing machine, PCB, player, microwave, mobile, television and speaker. There were about 3600 pictures with 300 images of battery, 300 images computers, 300 images keyboards, 300 images microwaves, 300 images mobiles, 300 images mouse, 300 image PCB, 300 images players, 300 images printers, 300 images speakers, 300 images washing machine and 300 images television were processed, trained, tested and evaluated for performance [16]. These divisions were made depending on the pictures contained in the separate respective folder. Figure 2 below are images of some of the dataset that used for this research. Classified as battery, computer, keyboard, mouse, printer, washing machine, pcb, player, microwave, mobile, television and speaker. There were about 3859 images and 3139 was used for training the model, 360 images each was used for validation and testing the model with 360 images of battery, 310 images computers, 330 images keyboards, 320 images microwaves, 330 images mobiles, 322 images mouse, 330 image PCB, 321 images players, 330 images printers, 306 images speakers, 324 images washing machine and 326 images television as shown in figure 1 the dataset of images.

Figure 1: Dataset Images of e-waste Categories

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We have collected the dataset by web scraping and Kaggle dataset site as there is no existing dataset for twelve different categories as a single file

2.2 The proposed Model

The study uses sequential neural network (SNN) architecture of deep learning algorithm to prepare four (4) mother-class, and each mother class contain three (3) categories of e-waste dependents of battery, computer, keyboard, mouse, printer, washing machine, PCB, player, microwave, mobile, television and speaker. Twelve convolutional neural networks are prepared into four blocks (A, B, C and D) each which contains three of the classes of the e-waste components one for each mother class, which will also prevent the recognition of a class that doesn't exist. For instance, if the mother class is computer, at that point we realize that the child class can't be a battery. At first, this model gets the image as input; at that point, the SNN creates the bounding box and the mother-class as an output. With that data, the real image is being cropped, which is one of CNN's input identified with the mother-class. After that, the output generated is the child class, which converged with the mother-class, and creates the formation of the final class. Finally, before the detection of the model, the output gets predicted with the bounding box. The mechanism of this model can be found in Fig 2 below

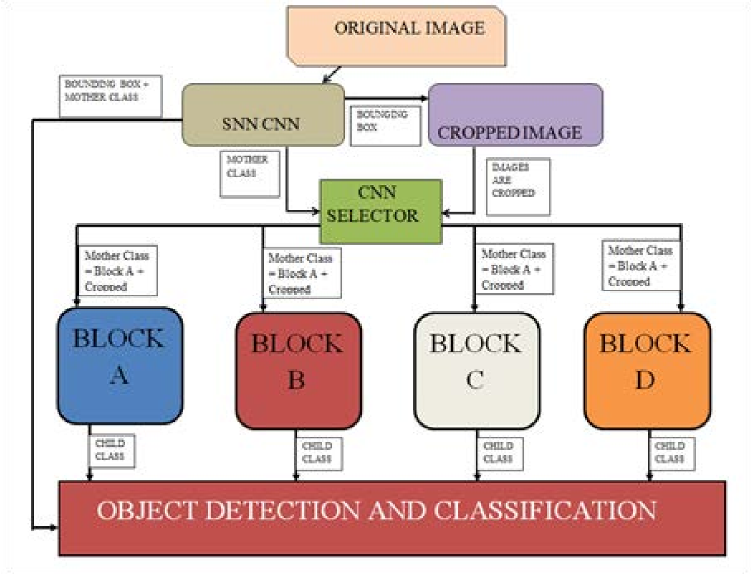

Figure 2: Sequential Neural Network Architecture

A Sequential Neural Network is a type of neural network architecture in Keras, a popular deep learning library. It's a linear stack of layers, where each layer is a fully connected neural network with an activation function. The output from one layer is used as input to the next layer, allowing the network to learn complex representations of the input data. The diagram depicts a hierarchical Convolutional Neural Network (CNN) architecture designed for object detection and classification, specifically applied to e-waste.

2.3 Model Development

The Sequential Neural Network Model was classified as battery, computer, keyboard, mouse, printer, washing machine, PCB, player, microwave, mobile, television and speaker. There were about 3859 images and 3139 was used for training the model, 360 images each was used for validation and testing the model with 360 images of battery, 310 images computers, 330 images keyboards, 320 images microwaves, 330 images mobiles, 322 images mouse, 330 image PCB, 321 images players, 330 images printers, 306 images speakers, 324 images washing machine and 326 images television (6) were processed, trained, tested and evaluated for performance. These divisions were made depending on the pictures contained in the separate respective folder.

Layer (type)	Out Put Shape
rescaling_5 (Rescaling)	(None, 224, 224, 3)
conv2d_15 (Conv2D)	(None, 222, 222, 16)
max_pooling2d_15 (MaxPooling2D)	(None, 111, 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_17 (MaxPooling2D)	(None, 26, 26, 64)
flatten_5 (Flatten)	(None, 43264)
dense_10 (Dense)	(None, 128)
dense_11 (Dense)	(None, 12)
Total params: 5,563,052 (21.22 MB) Trainable params: 5,563,052 (21.22 MB) Non-trainable params: 0 (0.00 B)	

Table 1: Model Architecture

The model architecture displayed in table 1 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 is typical for image classification tasks, leveraging convolutional layers for feature extraction and dense layers for classification.

2.4 Model Training

The Training Data is generated by generating tensorflow which contain all the data for the train and test images and 82% of images for every category in the whole dataset of e-waste images are used for training. The other 18% of the images are for the testing and validation phase. The whole purpose of this particular system is to make the framework figure out how to detect objects [17]. After the training data is generated, a label map is created which notified the system about what each object is by characterizing a mapping of class ID numbers to class names. After the label map is created, finally, the object detection pipeline is configured which helped in defining what type of parameters and models is used for training. Once the training pipeline is successfully built up and configured, TensorFlow started initializing the model training. A lot of computational power is required for training an enormous network in SNN. For preparing our neural network training, we used a HP Laptop outfitted with an Intel core i5 processor. Along with Python version 3.9, open-source software is used for high-performance mathematical calculations. Its adaptable architecture allows easy deployment of calculations over a variety of stages.

```
Epoch 1/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 174s 2s/step - accuracy: 0.1427 - loss: 2.7717 - val_accu
racy: 0.3778 - val_loss: 1.7607
Epoch 2/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 158s 2s/step - accuracy: 0.4258 - loss: 1.7698 - val_accu
racy: 0.5667 - val_loss: 1.3104
Epoch 3/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 157s 2s/step - accuracy: 0.5937 - loss: 1.2453 - val_accu
racy: 0.6472 - val_loss: 1.0722
Epoch 4/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 157s 2s/step - accuracy: 0.7348 - loss: 0.8376 - val_accu
racy: 0.7139 - val_loss: 0.9693
Epoch 5/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 157s 2s/step - accuracy: 0.8186 - loss: 0.5491 - val_accu
racy: 0.6556 - val_loss: 1.0813
Epoch 6/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 157s 2s/step - accuracy: 0.8980 - loss: 0.3237 - val_accu
racy: 0.6500 - val_loss: 1.3656
Epoch 7/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 165s 2s/step - accuracy: 0.9274 - loss: 0.2413 - val_accu
racy: 0.6889 - val_loss: 1.2966
Epoch 8/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 158s 2s/step - accuracy: 0.9418 - loss: 0.2288 - val_accu
racy: 0.6889 - val_loss: 1.2570
Epoch 9/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 160s 2s/step - accuracy: 0.9804 - loss: 0.0653 - val_accu
racy: 0.7139 - val_loss: 1.4799
Epoch 10/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 158s 2s/step - accuracy: 0.9902 - loss: 0.0566 - val_accu
racy: 0.7000 - val_loss: 1.3832
```

Figure 3: Model Training of 1-10 Epochs

Figure 3 analysis details the training and validation metrics of a deep learning model with 20 epochs. The study highlights the observed trends in accuracy and loss for both training and validation sets. Significant findings related to overfitting are discussed, and recommendations for mitigating this issue are proposed. The ultimate goal is to provide a comprehensive understanding of the model's learning behavior, aiding in the optimization of its performance for potential deployment as an application.

Plotting Performance

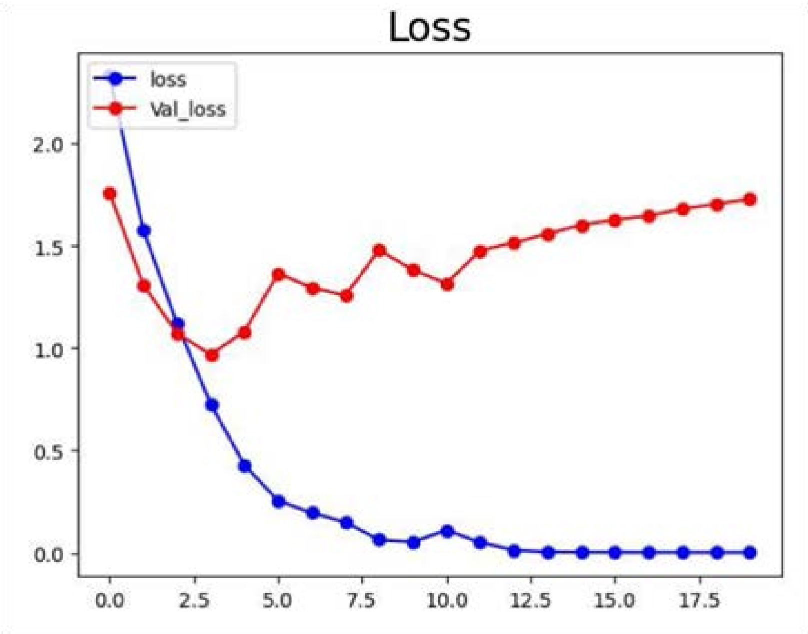

Figure 4: Loss Performance Graph

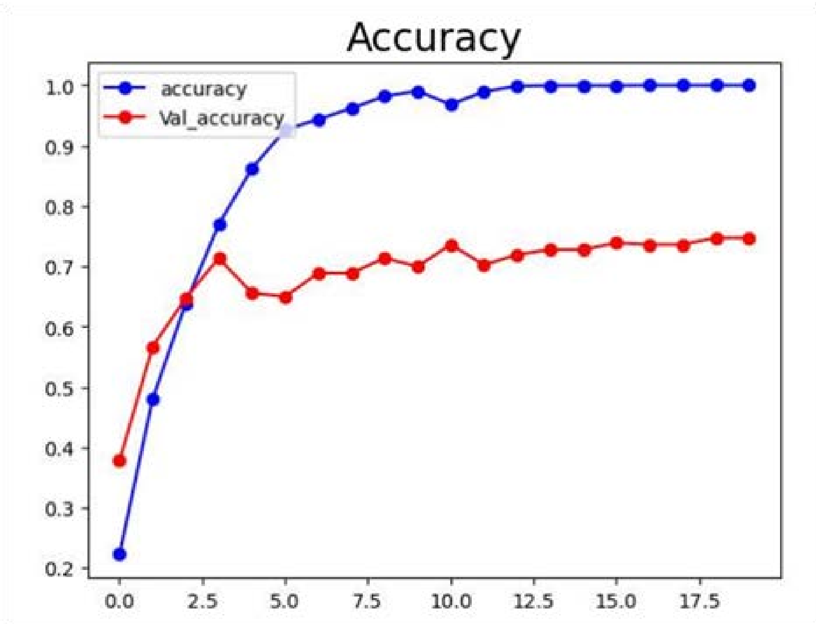

Figure 5: Accuracy Performance Graph

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. Training involves minimizing a loss function through iterative updates using gradient descent or its variants, as shown in Figures 4 and 5.

2.5 Evaluation metrics

To assess the performance of the model, the experiments employ the most common evaluation metrics, including accuracy, precision, recall, F1-Score, and confusion matrix [18]. The confusion matrix in figure 6, is a crucial evaluation tool in the context of e-waste classification. It provides a comprehensive assessment of the performance of a e-waste classification model by displaying the predicted outcomes against the actual class labels of the data [19]. The confusion matrix is structured into four distinct quadrants: The quadrant of true positives (TP) signifies the accurate identification of e-waste categories. Complementary to this, the quadrant of false positives (FP) denotes e-waste categories that were inaccurately classified. True negatives (TN) indicate the precise classification of e-waste categories. Conversely, the quadrant of false negatives (FN) represents the misclassification of e-waste categories.

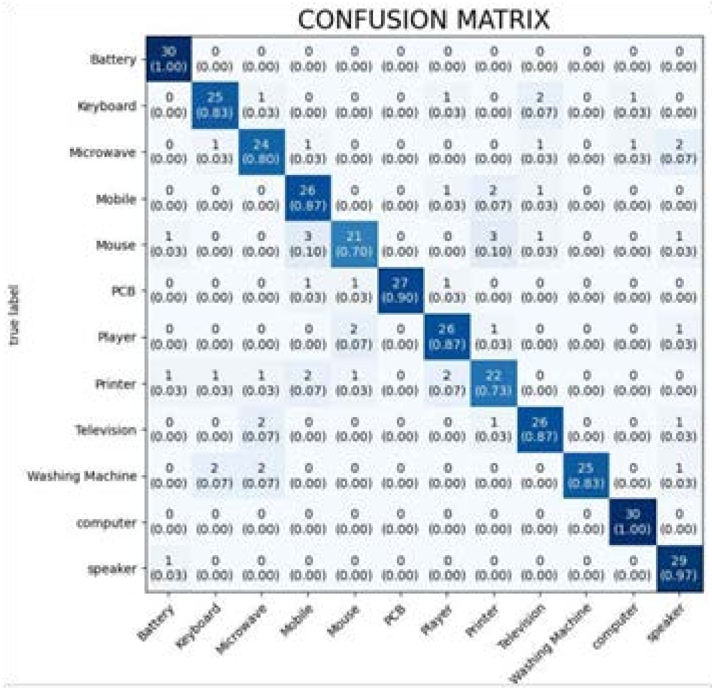

Figure 6: The Confusion Matrix of the Proposed Model

Each row represents a specific class of objects, and the columns list the precision, recall, F1-score, and the support for each class. Additionally, overall performance metrics, including accuracy, macro average, and weighted average, are also provided. Table 2

	precision	recall	F1-score	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	0.87	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

Table 2: Summary of Evaluation Report of Various Metrics

Accuracy represents the proportion of correctly classified instances [20], while precision measures how well the model can detect positive cases correctly among all the cases that it predicted as positive [21], and recall is a measure of how well a model can identify positive cases out of all those that are actually positive [22]. The F1-score indicates a balanced assessment of performance because it takes into account both recall and accuracy [23]. These evaluation metrics provide an extensive overview of the efficiency of our model in classification tasks.

3. Results and Discussion

The model's accuracy for the test set was 86%, demonstrating its robustness. The precision score was calculated to be 87%, indicating a high percentage of positively classified events that were correctly identified. The model's capacity to precisely identify real positive instances was demonstrated by the recall score of 86%. The F1-score was 86%, demonstrating a high degree of correlation between the predicted and true labels. The confusion matrix provides specific information about how well the model classified each class. Some e-waste components below were tested and they all predicted correctly with high accuracy.

After the design, development, training and evaluation of the model with different metrics it was incorporated into vscode with streamit to test and predict the accuracy of each component. The various components were tested and some predicted correctly with high probability of accuracy, ten out of the twelve categories that were used for the training process predicted correctly. The model can now be deploy for use in the classification of e-waste into various components environmental sustainability and eco-friendly that is devoid of e-waste which has become a threat to the environment and human lives. Also the data security of some e-waste components such as mobile and computer can be checked before the disposal of such component either for recycling, refurbishing, reuse or destruction so that the issues of data theft by unauthorized persons can be a reduced or be a thing of the past. Below are the screenshot of some of the tested e-waste components that were predicted correctly with various degrees of accuracy. Figure 7 and 8 are some of the screenshot of the tested and predicted e-waste components with probability of accuracy.

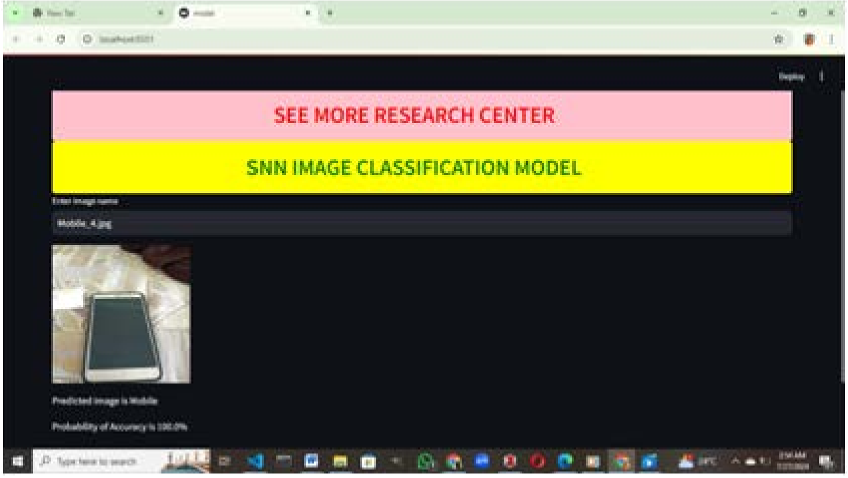

Figure 7: Mobile

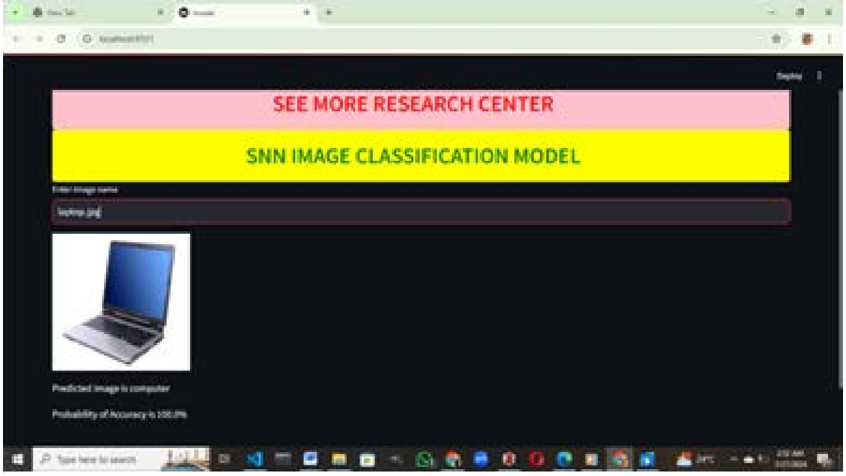

Figure 8: Laptop

4. Conclusion

The implementation of a deep learning model for e-waste management, as explored in this study, underscores the significant advancements that AI can bring to environmental sustainability efforts. Our model, developed using TensorFlow and Keras, achieved impressive performance metrics: an overall accuracy of 87%, precision of 87%, recall of 86%, and an F1-score of 86%. Despite some misclassifications, the high accuracy rates for most categories illustrate the robustness and reliability of the model. This system can be integrated into applications to facilitate the classification and processing of e-waste, aiding in recycling and data security. Future work should focus on addressing the misclassification issues and expanding the dataset to include a broader range of e-waste components, ensuring even greater accuracy and applicability. The success of this project advocates for the continued integration of deep learning technologies in environmental management systems, paving the way for smarter and more efficient waste handling solutions.

References

1. de Souza Lima, A. L., von Wangenheim, C. G., Martins, O. P., von Wangenheim, A., Hauck, J. C., & Borgatto, A. F. (2024). A Deep Learning Model for the Assessment of the Visual Aesthetics of Mobile User Interfaces. *Journal of the Brazilian Computer Society, 30*(1), 102-115.
2. Huynh, M. H., Pham-Hoai, P. T., Tran, A. K., & Nguyen, T. D. (2020, November). Automated waste sorting using convolutional neural network. *In 2020 7th NAFOSTED Conference on Information and Computer Science* (NICS) (pp. 102-107). IEEE.
3. Konyeha, S., Mughele,E.S, & Usip,P.U. (2019). A FRAMEWORK FOR THE ENVIRONMENTAL MANAGEMENT OF ELECTRONIC WASTE. *World Journal of Applied Science and Technology,* Vol. 11 No. 1 (2019). 29-34 29, Vol. 11(1), 29–34.
4. OISE, G. (2023). A Web Base E-Waste Management and Data Security System. *RADINKA JOURNAL OF SCIENCE AND SYSTEMATIC LITERATURE REVIEW, 1*(1), 49-55.
5. Sankhla, M. S., Kumari, M., Nandan, M., Mohril, S., Singh, G. P., Chaturvedi, B., & Kumar, D. R. (2016). A Web Base E-Waste Management and Data Security System. *IOSR Journal of Environmental Science, Toxicology and Food Technology, 10*(09), 98-104.
6. Devi, R. S., Vijaykumar, V. R., & Muthumeena, M. (2018). Waste segregation using deep learning algorithm. *Int. J. Innov. Technol. Explor. Eng, 8,* 401-403.
7. Kolsch, A., Afzal, M. Z., Ebbecke, M., & Liwicki, M. (2017, November). Real-time document image classification using deep CNN and extreme learning machines. In 2017 14th IAPR international conference on document analysis and recognition (ICDAR) (Vol. 1, pp. 1318-1323).
8. Kittali, R. M., & Sutagundar, A. (2016). Automation of waste segregation system using PLC. *International Journal on Emerging Technologies, International Journal on Emerging Technologies (Special Issue on ICRIET-2016) 7*(2): 265-268.
9. Misra, D., Das, G., Chakrabortty, T., & Das, D. (2018). An IoT-based waste management system monitored by cloud. *Journal of Material Cycles and Waste Management, 20*(3), 1574-1582.
10. Yu, Y., Jin, K., Zhang, H. C., Ling, F. F., & Barnes, D. (2000). A decision-making model for materials management of end-of-life electronic products*. Journal of Manufacturing Systems, 19*(2), 94-107.
11. Agarwal, C., Yewale, B., & Jagadish, C. (2020). Automatic waste segregation and management. *International Journal of Engineering Research & Technology (IJERT), 9*(6).
12. Voskergian, D., & Ishaq, I. (2023). E-Waste Tracker: A Platform to Monitor e-Waste from Collection to Recycling. In M. Tabaa, H. Badir, L. Bellatreche, A. Boulmakoul, A. Lbath, & F. Monteiro (Eds.), New Technologies, Artificial Intelligence and Smart Data (Vol. 1728, pp. 88–103). *Springer Nature Switzerland.*
13. Perfectson, O. G. (2024). Environmental and Information Safety of End-of-Life Electronics. *International Transactions on Electrical Engineering and Computer Science, 3*(2), 86-91.
14. Sileyew, K. J. (2019). *Research design and methodology* (Vol. 7, pp. 1-12). London: Cyberspace.
15. Akshat Tamrakar. (2023). E Waste Dataset. Kaggle online Repository.
16. Nowakowski, P., & Pamuła, T. (2020). Application of deep learning object classifier to improve e-waste collection planning. *Waste Management, 109*, 1-9.
17. Abdu, H., & Noor, M. H. M. (2022). A survey on waste detection and classification using deep learning. *IEEE Access, 10*, 128151-128165.
18. Mohammed, C. N., & Ahmed, A. M. (2024). A semantic-based model with a hybrid feature engineering process for accurate spam detection. *Journal of Electrical Systems and Information Technology, 11*(1), 26.
19. Hossain, F., Uddin, M. N., & Halder, R. K. (2021, April). Analysis of optimized machine learning and deep learning techniques for spam detection. *In 2021 IEEE International IOT, Electronics and Mechatronics Conference* (IEMTRONICS) (pp. 1-7). IEEE.
20. Madhavan, M. V., Pande, S., Umekar, P., Mahore, T., & Kalyankar, D. (2021). Comparative analysis of detection of email spam with the aid of machine learning approaches. *In IOP conference series: materials science and engineering (Vol. 1022, No. 1, p. 012113). IOP Publishing.*
21. Elhussein, M., & Brahimi, S. (2021). Clustering as feature selection method in spam classification: uncovering sick-leave sellers. *Applied Computing and Informatics.*
22. Gadde, S., Lakshmanarao, A., & Satyanarayana, S. (2021, March). SMS spam detection using machine learning and deep learning techniques. *In 2021 7th international conference on advanced computing and communication systems* (ICACCS) (Vol. 1, pp. 358-362). IEEE.
23. Nandhini, S., & KS, J. M. (2020, February). Performance evaluation of machine learning algorithms for email spam detection. *In 2020 International Conference on Emerging Trends in Information Technology and Engineering* (ic-ETITE) (pp. 1-4). IEEE.