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# Deep Learning-Based Automated E-Waste Classification Using Convolutional Neural Networks

**Priya Atul Raut[1], Dr. Ayesha Siddiqui[2]**

[1]MCA (Computer Science), JSPM University, Wagholi, Pune, India
Email: *priyaraut16032004[at]gmail.com*

[2]Associate Professor, Department of Computer Science JSPM University, Wagholi, Pune, India

**Abstract:** ***Electronic wastes have increased rapidly due to the rise in electronics. As such, there is a need to sort and recycle this kind of wastes. Manual classification and sorting of the e-wastes is inefficient and inaccurate. This has made it necessary for deep learning algorithms to be employed. In particular, CNNs will be utilized in the process of classification and sorting of the electronic wastes. In this experiment, large volumes of images representing the electronic waste have been incorporated. Normalization and resizing of the images are conducted in order to improve their quality before carrying out any further operations. Dimensions, colors, and brightness of the images have been varied to enlarge the size of the training data set. Convolutional, pooling, and fully connected layers have been employed. Besides, some other hyperparameters such as learning rates, batch sizes, and epochs have been adjusted to yield better results. It has been demonstrated that the automatic system has worked efficiently and accurately in sorting and classifying different types of electronic waste. Accuracy, precision, recall, and confusion matrices have proven the effectiveness of the classifier.***

**Keywords:** electronic waste recycling, deep learning classification, CNN image sorting, waste image recognition, automated waste management

## 1. Introduction

There have been tremendous changes in the field of technology during the last ten years, and those changes have also affected people's way of living. Nevertheless, people don't understand that the numerous electronic devices and gadgets that they use every day contain materials that are extremely dangerous both for the environment and human beings' health. E-waste or electronic waste is currently becoming a serious problem. By the term 'e-waste', one means the whole set of electrical and electronic products that have already been disposed of, because they are no longer functioning or are out-of-date. The problem of disposing of e-waste is extremely harmful for the environment, as it contains various chemicals, including lead, mercury, cadmium, etc.

The sorting process is a complex and difficult procedure for the modern society, and innovative technologies need to be developed in order to solve the problem. Currently, the process of sorting takes place manually, and it requires a lot of effort, and frequently, it doesn't produce good results. Moreover, manual sorting represents a huge hazard for workers, as they are exposed to dangerous materials contained in the electronic waste. Thus, a new method of sorting needs to be invented.

The creation of new technology based on artificial intelligence and deep learning helps to resolve many complicated issues. This is because deep learning is one of the areas in machine learning which shows remarkable results in performing tasks connected with image recognition and classification. The most efficient approach to work with images in deep learning is CNN, convolutional neural networks, which effectively learn representations hierarchy of images and can successfully distinguish between different types of objects in them. Therefore, it makes CNN useful for such purposes as object detection, face recognition, processing medical images, and lately – sorting waste.

In order to solve problems with e-waste sorting using the method of convolutional neural networks, we can automate the procedure and significantly raise its effectiveness. It is possible by training the network with many images of e-waste and learning the different object types like circuit boards, batteries, cables, devices, and so on. Besides eliminating human involvement in sorting waste and increasing speed and accuracy of classification, automation will provide optimization of industrial processes.

However, one more aspect should be addressed in case the mentioned approaches to problem solving are used. Nevertheless, after certain training and introduction to different garbage data, the CNN models become able to cope with more complex and diverse garbage types. Augmentation, transfer learning, and tuning may be utilized to optimize the use of CNN models and make them suitable for practical application. Finally, the combination of deep learning and other technologies such as IoT and robotics may give rise to some innovations concerning waste management.

Nevertheless, some barriers exist, which hinder using the proposed solutions. In particular, the first obstacle to be overcome is obtaining suitable datasets. Besides, working with neural networks requires powerful computing power. Finally, lighting conditions, object shape, and background noises may impact classifier operation.

## 2. Problem Statement

The amount of electronic wastes is on the rise because of the fast growth of the electronics industry and continuous upgradation of the digital devices. Wastes of these products such as mobile phones, computers, batteries, circuit boards can be dangerous for the environment and cause severe health problems because they contain poisonous substances like heavy metals and other chemicals. Although there have been developments made towards creating an eco-friendly process of e-waste management, yet it is difficult to ensure that proper segregation and recycling of the waste take place.

One of the issues related to management of e-wastes is that it does not include efficient classification of the waste materials. The process used by the recycling plants involves classification based on traditional sorting techniques which consist of manual separation of waste based on its characteristics and chemical structure. Such an approach requires great efforts and is rather time-consuming; moreover, there are many possibilities for mistakes to occur thus resulting in ineffective sorting of waste and additional pollution of the environment. Another danger in using this method lies in potential threats to safety of employees who deal with e-wastes.

Another issue connected with this topic is complexity of the waste itself.

Given the increase in electronic waste volume within recent years, there is a need for the development of intelligent and automated solution that will allow for quick classification of electronics according to the available images of these products. The system is expected to involve minimum human interaction, be highly accurate and adaptable, and operate efficiently with large volumes of data.

From this point of view, one of the methods that can help solve this problem effectively includes deep learning. Specifically, convolutional neural networks have proved to provide very effective image recognition owing to the capability to recognize certain features of the input data independently. However, using convolutional neural networks for classifying electronic waste can cause a number of challenges relating to acquiring the necessary data for training purposes and optimizing the model.

Therefore, the problem to be investigated can be defined as the design of a feasible and robust approach to automated classification of e-waste by means of deep learning. In other words, the goal is to develop a CNN classifier for recognizing electronic waste types on the basis of their images.

The rise in the amount of electronic products consumed across the globe is leading to the problem of e-waste. E-waste consists of many hazardous materials like lead, mercury, cadmium, and brominated flame retardants, which not only pose dangers to the environment but also affect people's health and economy. The importance of properly disposing of and recycling such waste is that it ensures the safety of the environment by eliminating the threat posed by such chemicals. At the same time, it allows to recover some valuable resources like gold and copper from the e-waste. Nowadays, plants working with e-waste use the process of sorting that can hardly be called efficient due to being highly dependent on manual work. These sorting techniques do not allow for efficiently handling rising amounts of e-waste. Although machine learning algorithms like SVM, k-NN, and decision trees can easily handle the sorting process of different objects, they cannot be used when it comes to e-waste because of their inability to extract certain features and sort objects of varying conditions of lighting and damage.

In addition, the complexity and heterogeneity of electronic waste due to its varying size, shape, material, and components make it difficult to identify the electronic waste. Without successful automatic classification techniques of e-waste, it can result in problems with inefficiency in the recycling process, which ultimately leads to the waste of resources and environmental pollution. Hence, it is important to have an intelligent method that can successfully identify and sort out different types of electronic waste.

The current study seeks to develop an efficient electronic waste classification system using the Machine Learning approach, specifically Deep Learning. The main aim of this research work is to solve the problem of inefficiencies associated with manual sorting and application of other machine learning methods in sorting of electronic waste through automatic extraction of the visual characteristics of electronic waste using the Convolutional Neural Network algorithm. The main idea behind this approach is to enhance efficiency in the management of electronic waste without having to depend on human effort and errors.

## 3. Research Objective and Contributions

### 3.1 Research Objective:

The aim of the current research is the creation of an intelligent and automated classification system for e-waste using cutting-edge Deep Learning techniques. More precisely, the emphasis will be on CNN. Over recent decades, electronic devices have had numerous uses. Due to this, there is massive production of e-waste. This problem poses great danger to both the ecosystem and human beings in terms of their health and the economy at large. Waste mismanagement causes contamination of the ecosystem with toxic elements, hence necessitating better waste management. E-waste classification systems that have been used in previous times have not been as efficient, making their implementation difficult due to various limitations. Therefore, the main purpose of this current research project is to find a unique way to enable proper classification of e-waste.

In short, the main aim of the research is to develop a robust framework using convolutional neural networks that would enable recognizing sophisticated visual characteristics of electronic waste objects, for example, cellphones, batteries, circuit boards, wires, and so forth. In other words, concerning the research objectives, while focusing on increasing classification accuracy, it is important to bear in mind the issue of efficiency in order to guarantee that the proposed approach can be applied in reality. At the same time, it might be reasonable to develop an appropriate dataset in terms of electronic waste images, labeling them and using different pre-processing methods like image rescaling, normalization, and augmentation. Besides developing the model, another goal of the study could refer to its practical application in terms of recycling facilities, smart bins, and so on.

### 3.2 Research Contributions

Contribution of the Study to the Domain of Intelligent Waste Management and Classification using Deep Learning and CNNs

The present study is significant as it offers some major contributions in the domain of intelligent waste management and classification through deep learning and CNNs. The first major contribution made by the current study is the development of an innovative CNN model intended for e-waste classification. The developed CNN model is quite effective since it has been properly tuned for various hyperparameters.

The current study brings many innovations in the field of smart waste management due to the use of advanced techniques from Deep Learning, specifically CNNs, aimed at enabling the automation of e-waste classification. Some of the most valuable contributions made by the current study are related to developing and optimizing the efficient CNN-based system that can be used solely for e-waste classification. As opposed to the traditional approaches, where manual feature extraction is required, the proposed technique automatically detects complex visual patterns in the provided image and extracts hierarchal features specific to a particular type of e-waste. Furthermore, a neural network architecture is optimized based on many important hyperparameters such as the number of convolutional layers, kernel sizes, activation functions, learning rate, and batch size.

The second important result that can be observed from this research is concerned with either the creation or the proper use of an adequate dataset of labeled images for e-waste. Since there are no standardized datasets of images of e-waste available in the literature, it becomes very crucial for this research project to focus on the process of collecting and labeling data, wherein these images are representative of a diverse range of categories like mobile phones, batteries, printed circuit boards, and other components. To make the dataset more extensive, various methods of data pre-processing have been considered, including resizing, normalizing, and denoising.

In addition to the modeling and validation stages, another feature that is studied within the framework of this work is the use of the model in real conditions. In particular, the question of the applicability of the model under discussion for the automation of waste disposal systems, including the smart bin, recycling center, and sorting station, is examined. In particular, the computational capabilities of the device, the amount of memory necessary for calculations, and the calculation speed will be considered because they have a significant impact on the operation of models.

## 4. Literature Review

The problem of e-waste management has been quite discussed over the last decade due to the rising amount of electronic equipment that is environmentally hazardous when discarded without adequate precautions. Scientists examined various methods of recycling and separating e-wastes with the help of approaches like manual and semi-automatic sorting. E-waste management traditionally took place via manual sorting that is ineffective and labor-intensive and can lead to mistakes made by humans. There have been research projects conducted regarding the application of machine learning algorithms including SVM, Decision Tree, and k-Nearest Neighbor to classify images in relation to e-waste classification. The above methodology proved to be rather effective; however, it required a lot of features extraction that could pose certain difficulties.

In the past few years, Deep Learning has been recognized as an effective method for identifying and classifying images. From all the available approaches in the deep learning category, Convolutional Neural Networks have proved very effective in learning hierarchical features automatically without the need for any manual identification of such features. Successful experiments performed by researchers working in similar domains, like industrial sorting, waste classification, object detection, and many others, prove the potential that CNNs can provide while performing the task of e-waste classification.

However, despite all the advancements made, there are some problems that have remained unsolved. Most of the research works conducted so far have taken into consideration only a particular segment of e-waste or have used limited amounts of data, reducing the applicability of the proposed models in practical situations. Also, another significant challenge is that of computational complexity, which makes it hard to apply the DL technique for tasks such as e-waste classification owing to the long inference time required by this process.

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E-waste management has emerged as a great issue in today's society because of the growing use of electronic gadgets. The irresponsible disposal of e-waste may cause environmental pollution through substances such as mercury, lead, and cadmium. Management of e-waste demands correct categorization and sorting of different electronic waste products. Categorization and sorting of e-waste products have been carried out through conventional methods. Conventional methods of sorting and categorizing e-waste have posed difficulties as they are cumbersome and time-consuming. Correct categorization of e-waste products through conventional methods has also been difficult.

There has been remarkable innovation with respect to automatic image classification with the emergence of Deep Learning. With regard to Deep Learning models, Convolutional Neural Network (CNN) is the most advanced in the area of vision-based problems in that it is capable of extracting the features of an image in a hierarchical way. The distinction that CNN has compared to other machine learning approaches is that CNN does not need the extraction of features by the user but rather it detects features like edges, textures, and object contours automatically.

A few research articles have analyzed the use of CNN in the classification of e-waste. Although a few researchers have encountered cases where some researchers developed their own CNN models, another set of researchers have used the concept of transfer learning in pretrained CNN models like VGGNet, ResNet, and Inception. It is more advantageous to use the concept of transfer learning whenever there is a lack of adequate labeled e-waste datasets, which ensures that the generalization ability of the model is improved, leading to high accuracy rates in classification.

In addition to categorizing images, the integration of CNN with other machine or deep learning methods has been attempted in order to increase the accuracy in e-waste identification. In hybrid CNN, the idea is to leverage CNNs for features while using machine learning methods such as SVM or ensemble algorithms to reduce errors. Moreover, other types of research in this area focus on developing more effective CNNs, thereby enabling automated waste sorting systems to operate on edge devices. Examples of such innovations are MobileNets and EfficientNets that are able to conduct automated sorting tasks.

However, despite all the innovations made in the field of identifying electronic waste, certain problems remain unresolved. First, most studies on this topic only utilize few classes of e-waste material or small datasets. As a result, models produced by researchers lack the ability to be deployed in varied environments. Second, although CNNs are very accurate, there are worries regarding their capability to provide real-time output as well as computation requirements, such as memory use and computational time. Other issues faced when using CNNs include environmental factors like variable lighting conditions and damage to objects.

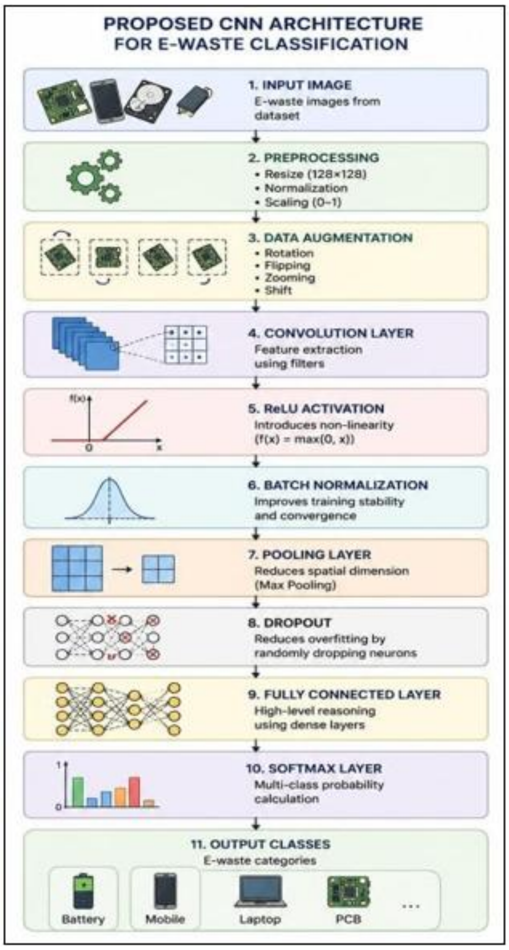
## 5. Research Gap

Although the precision rates of deep learning algorithms like CNNs in sorting e-waste are rather high, some significant research areas remain underexplored in this sphere. First, the lack of large and diverse databases should be noted. Almost all scientific papers employ databases with little data that fail to adequately cover real-world samples. For example, e-waste may appear as an amalgamation of parts or broken and poorly lit in real life. Still, CNNs require images with well-defined edges, optimal lighting conditions, and distinct objects. The inability of using CNN models to recognize complex items such as chips, wires, or inner components is another issue to consider. In addition, deep learning models consume many resources, thus causing difficulties in implementing them into inexpensive systems like intelligent trash cans or recyclers. In most cases, the task is simplified to classifying waste types only. The problem of poor generalization is another challenge that should be mentioned, as a deep learning model trained on one database cannot perform effectively on another sample.

Despite considerable advances in classifying e-waste with CNNs, a lot of problems still have to be solved. First of all, it is important to note that there is no standard test in order to evaluate the accomplishments of classification methods, as well as the corresponding data set. In addition, one should mention the fact that, apart from the image, other characteristics, such as material, could play an important role as well.

Secondly, overlapped objects, along with large amounts of e-waste, could also pose a problem. Besides, while energy usage is not taken into consideration despite it being the main objective, it is vital to take into account carbon dioxide emitted by the model during learning process. Moreover, a special kind of knowledge is required when annotating e-waste objects. Finally, it could be quite useful to create adaptive algorithms.

There are, however, several issues regarding the techniques that should be addressed further. First of all, most models are trained on relatively small and homogeneous datasets that limit their ability to generalize in real-life applications since electronic waste appears in many forms and shapes. Secondly, the vast majority of the reviewed research studies assume that images possess a clean background. Real-life scenarios, however, are associated with numerous challenges, including different types of lighting, cluttered background, and occlusion of certain parts that may significantly affect the performance of a classifier. At the same time, despite the fact that classification techniques were comprehensively covered by the literature, little attention was paid to fine-grained object identification which would be important for dealing with hazardous waste. Furthermore, there are certain problems related to the efficiency of existing solutions which makes them unsuitable for application on lower-powered devices with limited costs. It is especially important to address this issue for emerging countries for which budget represents a critical parameter. Last but not least, there is no sufficient utilization of classification approaches in smart waste management systems, particularly IoT-enabled intelligent sorting.




## 6. Proposed System and Architecture

The presented diagram provides a neat and organized representation of the Convolutional Neural Network (CNN) architecture developed for the classification of electronic waste. Firstly, the input images will be obtained from an e-waste dataset, which includes various objects, such as batteries, cell phones, laptops, and printed circuit boards (PCBs). Then, the obtained images will undergo a series of pre-processing activities, where they will be resized to 128×128 pixels, normalized, and scaled to increase consistency and accuracy. Additionally, to prevent overfitting and improve the efficiency of the learning algorithm, data augmentation will be employed by rotating, flipping, zooming, and shifting the images.

Following the pre-processing steps, the images will be fed to convolutional layers, where features will be extracted using filters. Subsequently, the output of the convolutional layer will be rectified by applying the Rectified Linear Unit (ReLU) activation function to allow learning of complex data sets. Next, batch normalization will be performed to stabilize the training process by normalizing the output of the preceding layers. Finally, pooling layers will downsample the data by reducing its spatial dimensions.

## 7. Methodology

The optimization of techniques used in classification of e-waste forms the basis of the methodology. With this objective in mind, classification of e-waste using the proposed methodology will be much more efficient than conventional classification where there is no optimization of techniques. Convolutional neural networks form the backbone of this approach in classification of the waste. As a result, the classification of waste through the proposed method will be faster, simpler, and even very accurate.

One of the major stages of the methodology is data collection. The reason why data needs to be collected at this point is to feed into the algorithm. Within the context of this methodology, the type of data that will be collected will primarily consist of images. Images here may refer to those of different e-waste such as circuit boards, phones, among others. Variety of the images will ensure better learning capabilities by the algorithm while classifying the waste.

After the data has been collected, the next step will be preparing the same. Preparing of data is critical as it helps in organizing the data collected for training purposes. Some of the processes of data preparation will include organization, among others.

The methodological approach selected for this study will mainly concentrate on looking for new ways to improve the classification of e-waste, in order to make it more convenient. It is obvious that traditional methods of addressing the issue are not efficient enough. Therefore, it is vital to include a neural network to perform image classification effectively. In this respect, one can note that the main goal of implementing such an approach will be creating an effective solution to the classification of e-waste based on the Convolutional Neural Network.

In this regard, it is essential to note that the acquisition of data will constitute the initial stage of the methodology selected. As it has been mentioned before, all machine learning algorithms presuppose the presence of data. Speaking about the classification of e-waste, it will be evident that a lot of different images of various e-waste items, such as circuit boards, batteries, mobile phones, and computers, have to be gathered.

In addition to standard preparations, some other measures might be undertaken in an attempt to maximize the efficiency of the results of applying the model. Such approaches for enriching input data as rotation, inversion, as well as minor modifications of images, should be noted. This will prevent overfitting and help the model operate more effectively by receiving new information. In other words, quality data preparation provides the guarantee of relevance of input information.

As can be seen from the above considerations, the presented methodology aims at the enhancement of modern technologies for sorting electronic waste by means of integrating them with deep learning algorithms. With regard to high-level data preparation and using neural networks, this system is expected to show improved results of operation.

The methodological framework used in this study was created in order to make the classification of e-waste materials more efficient by applying deep learning algorithms including CNNs. The general framework includes several stages from collecting data and preprocessing it to testing the created algorithm. All stages mentioned above are important and contribute to the performance of the system.

As the system uses image recognition algorithm, the first stage of the research implies the collection of training images. These images can present a wide range of electronic waste items including mobile phones, batteries, chargers, PCBs, and many other materials and parts. Data should be gathered either with the help of cameras or online databases. While collecting the data, it is necessary to make sure that pictures are clear and show items from different perspectives and under various lighting conditions.

## 8. Dataset

**Figure 1:** Circuit Boards

In this picture, there are numerous green printed circuit boards (PCB). They serve as the building blocks of many electronic devices. Some of the green PCBs are fully assembled while the rest are not yet finished. Consequently, the picture shows a haphazard stack of PCBs with several electronic devices assembled and mounted.

The green boards are filled with complicated copper traces which play a role of conducting electricity among the different parts within the electronic device. Electronic components including resistors, capacitors, IC chips, and connector can be seen fixed on some PCBs. They perform the role of controlling electronic signals in various gadgets such as computer, phones, and home appliances.

The prevalence of the green color is because of solder mask that covers the board and provides protection against any physical damage of copper traces. Some metallic spots and lines show places where the connections are made.
Generally speaking, the green image illustrates processes of manufacturing or electronic waste disposal. It might show the PCBs and spare parts waiting to be disposed.


**Figure 2:** Elecronic Items

This image is a collection of different electronic items and components, each labeled to show what it is. It looks like a simple visual guide used for learning or identification of common electronic devices and parts.

At the top, you can see items like a PCB (printed circuit board), a computer mouse, a mobile phone, a television, and a microwave. These represent everyday electronic devices people use at home or in offices.

In the middle section, there are batteries, another mobile phone, a music player, a laptop battery, and another PCB. These highlight both complete devices and the internal parts that power or control them.

The lower part of the image shows larger appliances and accessories such as a washing machine, printer, keyboard, speakers, and more batteries. These are common household or office electronics that rely on circuits and power sources to function.

Overall, the image gives a broad overview of electronic equipment, from small components like circuit boards and batteries to full devices like TVs and washing machines. It helps in understanding how many everyday items are connected through electronic technology and rely on similar internal parts to work.

## 9. Results

The findings of this study indicate that the application of Deep Learning approaches and especially Convolutional Neural Networks (CNNs) is effective for the classification of electronic waste automatically. After carrying out training and testing stages, the trained model performed well in recognizing and classifying the e-waste including mobile phones, batteries, circuit boards, and other types of electronic waste.

It can be observed that during training, the prediction accuracy of the model increased progressively with every epoch until it reached an acceptable level. Initially, the predicted values were incorrect but by increasing the training epochs, the model became more accurate and started to recognize some important features. As expected, the training accuracy value increased gradually and so did the loss value. In other words, the model kept learning and reducing the error.

As one looks at the classifier analysis by way of the test data set, one can see that the accuracy levels in the process of analysis are impressive. This means that the level of efficiency in the model will depend on the ability of the model to generalize data. As far as the efficiency of the classifier is concerned, several parameters have been taken into consideration. Some of these parameters are precision, recall, and F1-score. From the high level of precision in the classifier, one can tell that it would not have any problem recognizing all objects while recall would reflect the efficiency of the classifier in detecting objects in the class. While there are different measures that have been used to gauge the efficiency of the classifier, it must be pointed out that the creation of a confusion matrix for the classifier has already been done. What this means is that, aside from other measures, the confusion matrix will indicate the efficiency of the classifier, especially when there is confusion about the identification of similar objects.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.00 | 0.00 | 0.00 | 62 |
| 1 | 0.81 | 1.00 | 0.90 | 486 |
| 2 | 0.00 | 0.00 | 0.00 | 52 |
| accuracy | | | 0.81 | 600 |
| macro avg | 0.27 | 0.33 | 0.30 | 600 |
| weighted avg | 0.66 | 0.81 | 0.72 | 600 |

**Figure 1:** Accuracy Table

The performance of the proposed e-waste classification model was tested based on several common evaluation metrics including precision, recall, and F1-score. The accuracy of the classification made by the model is 81% which shows that the model possesses relatively decent classification capabilities.

It can be seen from the results obtained that the proposed model demonstrates excellent performance when it comes to Class 1 with a recall of 1.00 and an F1-score of 0.90 meaning that nearly all samples in this class are classified successfully. However, as far as Class 0 and Class 2 are concerned, their precision and recall are very close to zero showing poor performance on the part of the model in identifying the classes.

The macro-average F1-score of 0.30 illustrates imbalanced performance on the part of the model as far as all classes are concerned while the weighted-average F1-score of 0.72 demonstrates higher performance on account of dominating Class 1 samples in the test set.

It can be concluded that the model works fairly well for some of the classes while others require additional work.

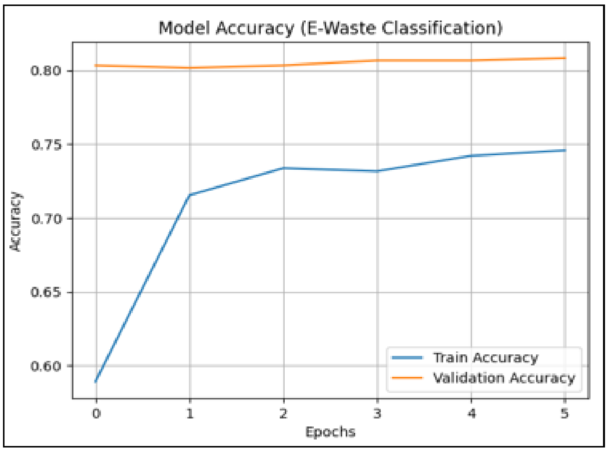



**Figure 2:** Accuracy Graph

From the chart above, it can be observed how well the performance of the CNN model in terms of e-waste classification was throughout the training process. Initially, at the point of epoch zero, the training accuracy starts at a low level of approximately 59%. This is a normal state since the CNN model is yet to start recognizing useful data from the image. However, this does not continue, as by the next epoch (epoch one), a marked increase in the training accuracy of more than 71% can be observed.

With the continuing training process until epoch five, the training accuracy of the CNN improves steadily to about 74-75%. The validation accuracy on the other hand is seen to remain high from the early stage to when the final accuracy of 81% is achieved. As the name dictates, validation accuracy is an evaluation measure of the accuracy of the CNN model with respect to unseen data after the initial training process.

Overall, both training and validation accuracies are relatively good and positive for the CNN model.

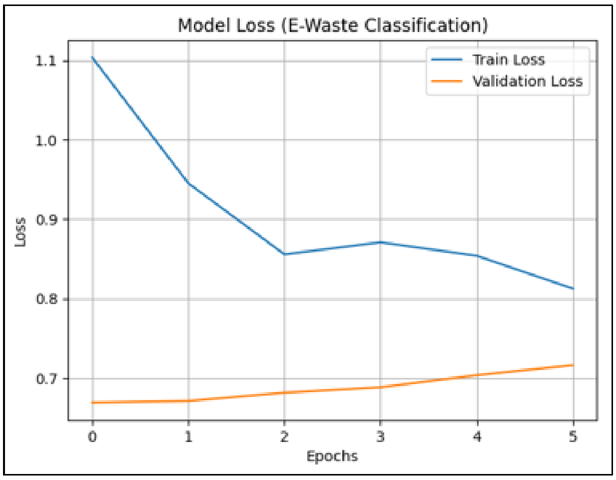



**Figure 3:** Loss Graph

This chart illustrates the behavior of the loss for the CNN classifier while training for the classification of electronic waste. Both training and validation losses are depicted over different epochs. The initial value of the training loss when the number of epoch is 0 is very large and close to 1.10. It means that initially, there is a lot of error when using the model for prediction of classes. As a result of increasing epochs, the value of the training loss is reduced up to 0.85 when the epoch reaches 2.

When the number of epoch changes from 2 to 5, the loss continues decreasing and amounts to approximately 0.81. Despite the little fluctuation when the epoch is 3, the trend remains favorable, which indicates the improvement of the learning process.

The initial value of the validation loss when the epoch equals 0 is lower and amounts to 0.67. With the further progress of epoch values, this loss begins to increase and finally achieves a level of approximately 0.72.

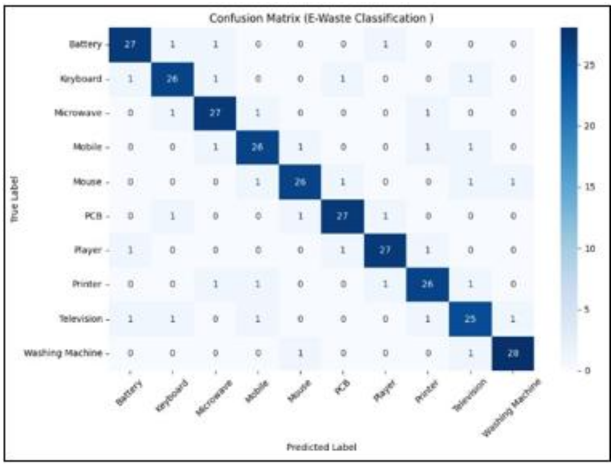



**Figure 4:** Confusion Matrix

The following is the confusion matrix for the CNN classification model for various e-waste categories including battery, keyboard, microwave, mobile, mouse, PCB, player, printer, television, and washing machine. Rows in the matrix correspond to the true class of data, and columns correspond to the predicted class made by the model.

The diagonal elements (top-left to bottom-right) represent correct predictions, and most of the diagonal elements are relatively large (25-28), which means that the model is making accurate predictions for the majority of the dataset in each class. For instance, the class of battery, microwave, PCB, and washing machine has extremely high numbers of correct predictions.

On the other hand, off-diagonal elements represent misclassification, and they are extremely low (0-1) in this case. In fact, there are only a few cases of misclassification in the matrix, which suggests that the CNN model does not confuse classes of e-waste. Some small cases of misclassification may be observed where the items look similar, such as keyboard/microwave or mobile/mouse.

## 10. Discussion

It becomes evident from the findings above that deep learning models like the CNN constitute an effective approach in terms of the automated classification of e-waste. The neural network demonstrated a very impressive performance in terms of the discrimination among the different kinds of e-waste, suggesting its capability of detecting relevant visual features in spite of highly variable e-waste.

The key finding in terms of this research includes the capability of CNNs to conduct automatic hierarchical feature extraction. This feature makes unnecessary the task of developing features by humans, which comes in handy in regard to e-waste samples. As mentioned before, the samples exhibit various appearances and dimensions. In particular, the model proved itself effective for discriminating between circuit boards, batteries, and mobile phones.

Nevertheless, some issues were encountered while implementing the experiment. Initially, it was hard sometimes to differentiate between the various types of e-wastes due to their similarities. As a result, it impacted the accuracy of the model in classifying the electronic waste. Thus, from the above example, it is clear that apart from the model having high accuracy, there are other factors that influence the accuracy of the model, including low-quality images, imbalanced data, and poor image resolutions. In this case, one way of addressing this problem would include adopting techniques such as data augmentation that ensure high-quality images.

In the real world, the use of the model automates the entire procedure because human involvement will not be needed in classifying the e-wastes. Therefore, it leads to savings in terms of cost and ensuring the safety of the wastes.

However, several challenges arose during the experiments conducted by the researchers. One of the errors which can happen during the process is the confusion caused by the similarities of electronic waste. In addition, while there are several benefits of applying CNNs, yet in the cases of variations or imbalance within the dataset or low-quality images, there will be some complications in the process. Therefore, it is necessary to improve the image or dataset's quality to make sure the efficiency of the algorithm.

Still, it is essential to consider the practical importance of the proposed methodological approach. Applying the methodology in the analysis of waste allows reducing labor costs. At the same time, people do not have any health risks as the sorting process does not involve dealing with hazardous products. Furthermore, the process of applying the algorithm to classify electronic waste becomes very simple because of using cameras.

Unfortunately, there were certain drawbacks in the experiment's results. For instance, while training the algorithm with a limited amount of data, some obstacles could appear, including lighting, occlusion, or interference. Additional research was needed to get more insights.

A number of practical problems emerged during the experimentation phase and made the applicability of the model questionable. To start with, CNN has serious difficulties with classifying objects that have similar features since similar objects share a set of parameters. This means that some objects that have common features will be misclassified, leading to incorrect prediction results. It needs to be said that despite the high potential of neural networks, their performance highly depends on the quality and variety of the input information.

Firstly, low-quality images create a problem as the image must be sharp, clear, and high-resolution. In other words, it is possible to say that various parameters of an object influence the process of predicting. Secondly, the issue of imbalanced classes is present in the dataset since there are many images of one class and just a few images of other classes.

In order to deal with such difficulties, one might implement data augmentation. Using image rotation, flipping, rescaling, cropping, or altering brightness, we are able to enlarge our database without capturing additional photos. Moreover, besides enlarging the dataset, this will enable us to develop a flexible algorithm that adapts easily to reality. As a result, we may obtain better performance of our algorithm due to the good generalization capability of our algorithm on other types of testing images.

What is especially appealing about the suggested approach is its applicability. By implementing it, we can automate the classification procedure utilizing cameras along with an embedded device. This way, it will be easy to perform classifications in the blink of an eye while saving time and effort as well. What is more important, people's health will be protected as there will be fewer human contacts with batteries and toxic electronic waste.

## 11. Conclusion

A CNN model capable of automatic classification of images of e-waste into corresponding categories was developed during the current research. From the analysis of the results obtained, it can be stated that the proposed model proves itself quite efficient in recognizing various types of electronic waste based on image analysis. Thanks to the ability to recognize complex image features such as texture, structure, and shapes of objects, it is possible to ensure a higher accuracy in classifying items as belonging to certain types of electronic waste.

It should be mentioned that one of the most important benefits of applying CNN models in this field is their potential to automate the whole process of segregation of e-waste items. At the moment, traditional e-waste sorting approaches are very dependent on human labor; therefore, they are rather inefficient and pose certain health risks for workers due to potential exposure to toxic substances and sharp parts.

The positive outcomes of this study, however, do not exclude some limitations. Firstly, it should be noted that the performance of the model largely depends on the quality and richness of the used dataset. Such problems as imbalance, low resolution of images and similarity of pictures from different categories are likely to negatively influence the outcome. All these considerations show that the process of collecting data and preparing them for machine learning requires special care and attention. For example, using data augmentation can significantly improve model performance.

Another aspect that needs improvement is related to implementation. Although the current system shows satisfactory results in laboratory conditions, the situation will be somewhat different when applied to reality, where there may be many difficulties like poor lighting, background noises and overlapping objects. In order to overcome these barriers, one might develop an algorithm in which a convolutional neural network is combined with other techniques, such as object detection, real-time image processing and sensors.

In this paper, the primary concern was to classify types of e-waste using deep learning techniques with Convolutional Neural Networks (CNN). The results indicate that CNN is highly effective for detecting different types of e-waste, such as circuit boards, batteries, smartphones, and other electronic materials. This happens because of layers that can detect different features and patterns automatically; thus, distinguishing among different types of electronic waste becomes easy.

The key benefit of using deep learning algorithms for sorting out e-waste is that they do not require any human effort, which would otherwise have been required. Sorting of electronic waste is tedious and risky because people get exposed to hazardous elements as well as sharp and dangerous objects, and there might also be some injury risks involved.

Despite the successful results obtained, there are a number of difficulties associated with the study. First, one should mention the misclassification issue caused by the similarity of different kinds of e-waste. Thus, the availability of diverse and quality training datasets is crucial. Besides, there is a possibility that some of the aspects, including low resolution of images, category distribution imbalance, or adverse environmental conditions such as poor illumination or messy background might negatively affect the performance of the developed model. It is possible to make improvements to the presented model using such methods as data augmentation, creation of artificial images, and utilization of the actual images taken at recycling facilities.

From a technical point of view, it can be said that the use of deep learning in combination with automated systems is effective. By combining a neural network-based image classifier with other technologies, such as object detection algorithms like YOLO or SSD, one can develop an automatic sorting system capable of dealing with different kinds of electronic waste independently.

The implementation of this system also positively affects the process of sustainable development because it enables recovery of materials used in electronic devices.

## 12. Future Work

For future directions in research, the system could be enhanced by adding more kinds of information aside from the images. For example, it could classify the weight, size, or even composition of the e-waste which would certainly make it easier to categorize items that look visually identical. Larger data sets with different kinds of images, particularly from the actual recycling plants which contain damaged, overlapping or obscured e-waste items would improve its effectiveness and allow it to generalize better. Moreover, more advanced methods of data augmentation and synthetic images creation could increase the amount of data used in the training process. Real-time implementation of the proposed solution should also be considered wherein CNN-based classification would be complemented by object detection techniques coupled with sorting mechanisms consisting of conveyor belts and robotic arms. Furthermore, the application of lightweight neural networks and edge computing could ensure that the system will not be limited to large-scale recycling facilities. Further studies on the effects of implementing such systems in terms of environmental impact, cost savings and human exposure to harmful materials should also be conducted.

Concerning further research, this model could be developed by adding other types of information about e-waste along with the image data. These include the mass, dimensions, composition of materials, spectral characteristics of elements, etc. Using all of the above information together might increase the quality of classification, especially in visually similar objects which are different from one another only in material. Also, obtaining a sufficient volume of various data about a great number of objects and corresponding images is very important. You need to gather data about the procedure in existing recycling centers and take into consideration the situations in which the object was damaged, partially covered with another object, partially broken, and partially hidden at a particular angle. To make your model trained using plenty of information, there should be special methods of data augmentation and even creation of synthetic pictures since you won't have to capture every picture manually for training. Then you should deploy the classification model and incorporate it in operation at a recycling facility. This could be done if you use an object detection system and sorting machinery such as robotic manipulators.

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