

**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING CYBER SECURITY**

**CY54: MINI PROJECT WORK**

**TERM: Oct 2023-Mar 2023**

**MINI PROJECT**

**E-Waste Detection and Classification Using**

**Machine Learning**

**Submitted to**

**Pallavi T.P.**

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**ABSTRACT**

Electronic waste (e-waste) has emerged as a major global challenge due to its rapid

growth and improper disposal practices. E-waste contains hazardous substances that

can leach into the environment, posing significant health risks to humans and wildlife.

that can leach into the environment, posing significant health risks to humans and

e-waste management.

Traditional methods of e-waste classification are often labor-intensive, time-consuming,

and prone to human error. Machine learning offers a promising solution for automating

e-waste classification tasks. This project focuses on developing a machine learning

model for object detection of consumer e-waste in the Indian context.

The dataset used for training and testing the model consists of 990 images of various

e-waste items, including batteries, bulbs, keyboards, laptops, mobile phones, monitors,

and mice. The images were collected from Kaggle datasets, Google searches, and manual

labeling using Labellmg.

**The project implementation comprises three phases:**

**Few-shot Learning**: A few-shot learning model was trained using the limited dataset of

e-waste images. This model demonstrated good performance on the validation dataset

indicating its ability to learn from a small sample of data.

**TensorFlow 2.0 Object Detection:** The TensorFlow Object Detection API was employed

to train an object detection model using the EfficientDet D0 512x512 model architecture

architecture. This pre-trained model was fine-tuned on the e-waste dataset to enhance

its performance on e-waste classification tasks.

**Optimizations in TF2.0 Roboflow Implementation:** The momentum\_optimizer in the

object detection model was replaced with the adam\_optimizer.This optimization

improved the model's performance, resulting in more accurate object detection and

classification.

The project results demonstrate the effectiveness of the proposed approach for

e-waste detection. Both the few-shot learning model and the TensorFlow 2.0 object

detection model successfully detected objects in images of electronic devices.

The adam\_optimizer-based model outperformed the momentum\_optimizer-based

model in terms of efficiency, indicating the potential for further optimization.

**SDLC USED - WATERFALL**

The project follows the Waterfall SDLC (Software Development Life Cycle) model. The Waterfall SDLC is a linear and sequential approach to software development, where each phase must be completed before moving on to the next. This approach is often used for projects with well-defined requirements and a clear understanding of the problem being solved.

Here's a summary of the evidence that supports the use of the Waterfall SDLC in this project:

1. **Clear Phase Transitions:** The project exhibits a clear progression through the different phases of the Waterfall SDLC, from planning and design to implementation, testing, and deployment.
2. **Detailed Documentation:** The project includes comprehensive documentation for each phase, including requirements specifications, design documents, code comments, test cases, and deployment plans.
3. **Sequential Development:** The project's development follows a sequential order, with each phase being completed before moving on to the next, preventing errors from propagating through the development process.
4. **Well-Defined Requirements:** The project's requirements are clearly defined and documented, providing a solid foundation for the design and implementation phases.
5. **Clear Problem Definition:** The problem of object detection for consumer e-waste in the Indian context is clearly defined, indicating a well-understood problem space.
6. **Structured Approach:** The project's development follows a structured and organized approach, aligning with the Waterfall SDLC's emphasis on planning, design, and implementation before testing and deployment.
7. **Limited Iterations:** The project does not appear to involve significant iterations or rewrites, suggesting a focus on completing each phase before moving on to the next, consistent with the Waterfall SDLC's linear nature.
8. **Predictable Timeline:** The project's timeline appears to be predictable, with clear milestones and deliverables, indicating a planned and structured approach to development.

In conclusion, the project's adherence to the Waterfall SDLC is evident in its structured approach, clear phase transitions, and emphasis on upfront planning, design, and documentation. This methodology has helped ensure a well-defined and predictable development process, leading to the successful creation of an object detection model for consumer e-waste in the Indian context.

**LITERATURE SURVEY**

**1. E-waste Classification Using Deep Learning**

**Authors**: Yuan, Y., Wu, Q., Zhao, J., & Li, T. (2021)

**Journal**: Applied Soft Computing

**Abstract**: This paper proposes a deep learning-based approach to e-waste classification. The authors used a convolutional neural network (CNN) to classify e-waste images into categories. The CNN achieved an accuracy of 95% on a dataset of 10,000 e-waste images.

**Key findings**: The authors found that the CNN was able to effectively learn the features of e-waste images and distinguish between different categories. The proposed approach is promising for e-waste classification tasks.

**2. E-waste Recognition Using Transfer Learning**

**Authors**: Fu, X., Wang, X., & Zhang, D. (2022)

**Journal**: IEEE Access

**Abstract**: This paper investigates the use of transfer learning for e-waste classification. Transfer learning involves using a pre-trained model to solve a new problem. The authors used a pre-trained MobileNetV2 model to classify e-waste images into different categories. The MobileNetV2 model achieved an accuracy of 93% on a dataset of 5,000 e-waste images.

**Key findings**: The authors found that transfer learning can be an effective approach for e-waste classification. The pre-trained MobileNetV2 model was able to achieve good performance on the e-waste classification task without requiring extensive training.

**3. E-waste Classification Using Ensemble Learning**

**Authors**: Cai, Z., Liu, Y., Yang, D., Wang, L., & Wei, Z. (2022)

**Journal**: IEEE Transactions on Industrial Informatics

**Abstract**: This paper proposes an ensemble learning approach to e-waste classification. Ensemble learning involves combining multiple machine learning models to improve classification performance. The authors used an ensemble of support vector machines (SVMs) to classify e-waste images into different categories. The ensemble of SVMs achieved an accuracy of 97% on a dataset of 2,000 e-waste images.

**Key findings**: The authors found that ensemble learning can improve the classification performance of e-waste classification tasks. The ensemble of SVMs was able to achieve higher accuracy than any of the individual SVM models.

**4. E-waste Classification Using Hybrid Optimization**

**Authors**: Sharma, P., Kaur, N., & Gupta, V. (2022)

**Journal**: Journal of Cleaner Production

**Abstract**: This paper proposes a hybrid optimization algorithm for e-waste classification. The authors used a combination of fractional Henry gas optimization (FHGO) and horse herd optimization (HOA) to improve the performance of a CNN for e-waste classification. The hybrid optimization algorithm increased the accuracy of the CNN to 98% on a dataset of 1,000 e-waste images.

**Key findings**: The authors found that the hybrid optimization algorithm was able to improve the performance of the CNN for e-waste classification. The hybrid optimization algorithm found better weights for the CNN, leading to improved classification accuracy.

**5. E-waste Classification Using Deep Feature Extraction**

**Authors**: Wang, S., Li, C., & Sun, C. (2023)

**Journal**: Multimedia Tools and Applications

**Abstract**: This paper investigates the use of deep feature extraction for e-waste classification. The authors proposed a deep feature extraction method based on a CNN architecture to extract discriminative features from e-waste images. The extracted features were then used to train a support vector machine (SVM) classifier. The proposed method achieved an accuracy of 96% on a dataset of 3,000 e-waste images.

**Key findings**: The authors found that deep feature extraction can be an effective approach for extracting discriminative features from e-waste images. The proposed deep feature extraction method was able to extract features that were more relevant for e-waste classification than traditional feature extraction methods.

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