Report(CDV11)-PC

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CHAPTER-1

INTRODUCTION

Electronic waste is one of the deadliest environmental threats to an advanced world. In large part because of rapid technological advancement and resultant obsolescence of electronic devices, vast heaps of electronic materials are getting thrown away or consigned into oceans and ground waste. Additionally, the wastage of the depleted natural resource besides environmental deterioration have been aggregated through unhygienic disposal and as a consequence from e-wastes, poisoning seep through toxic materials soil and water systems. Hence, finding a solution for this dual problem of waste management and resource conservation requires innovative approaches that combine technology, sustainability, and public engagement.

Fig 1 – Global E-waste Management

Our project using machine learning and web-based technologies to improve the responsible management of e-waste, "Improving Reusability of Electronic Components," is an innovative solution. In other words, it means making the usability of people's electronic components easy to check so that insights may be drawn from it, thereby encouraging the repair, reuse, or proper disposal of components. This focus on sustainability and user empowerment can bridge the gap between ecological responsibility and technological advancement.

The project is centered on a web application that easily allows users to upload images of electronic components. At the center of this system is a deep learning classification model, which was carefully trained on over 21,000 images of electronic components. This model is developed using TensorFlow and is expected to recognize a wide range of electronics, from laptops and smartphones to circuit boards and other typically discarded devices. There are three major conditions for determining the reusability of the component on which classification is based:

1. Partially Functioning: Pieces found in this group can be repaired or repurposed. The application provides recommendations for repair methods or alternative usages that extend the life cycle of the component.

2. Fully Functional: These parts are considered good enough for direct reuse or donation. The system encourages users to donate fully functional items to avoid waste and fulfill community needs.

3. Non-Functional (Disposable): For parts that cannot be repaired or reused, the application emphasizes proper recycling and guidelines for environmentally friendly disposal to minimize environmental impact.

A well-integrated deep learning model using Streamlit-based web application provides the ease of accessibility and usage for the user. The user is given immediate feedback on their uploaded images with step-by-step recommendations for further action. The use of a highly accurate model that has been trained on an extremely diverse dataset makes it possible to provide accurate classification results, aiding the user in making decisions for their e-waste.
This project can help considerably reduce the amount of environmental damage caused by e-waste by simplifying the assessment process and equipping people with knowledge. It fosters a culture of sustainability through promoting repair and reuse rather than disposal and creating awareness about the ecological implications of electronic waste. Furthermore, the solution is scalable in such a way that it could be adapted to different geographical and demographic contexts thus achieving global reach and impact.
In summary, "Improving Reusability of Electronic Components" is the pioneering effort that addresses the serious issue of e-waste. This project embodies a union between advanced machine learning techniques and user-centric design to provide practical and impactful solutions melding technological innovation with ecological stewardship. The project calls for responsible consumer behavior to contribute to building a green and sustainable future.

1.1 Electric Component Reusability

1.1.1 Overview:

This project brings into focus an important issue in the modern world of electronic waste (e-waste), using artificial intelligence to evaluate and classify the reusability of electronic components. Combining a powerful machine-learning model with an easy-to-use application interface, the system makes possible a very practical approach to sustainable e-waste management. [1]

1.1.2 Key Concepts:

1. Image-Based Classification:

This feature is the core of the system, enabling users to classify electronic components using images.

How It Works:

The user submits an image of an electronic component, such as a laptop, smartphone, or circuit board, via the web application. A trained convolutional neural network (CNN) then analyzes the uploaded image to categorize the component into one of the established categories. The model provides the predicted type of component along with a confidence score that reflects the accuracy of its prediction. [2]

Advantages:

Simplifies component identification for users without technical knowledge.

Copes with diverse component appearances, including worn or partially damaged items.

2. Reusability Assessment:

The system assesses the condition of the identified component and classifies it into one of three reusability conditions.

Categories:

- Fully Functioning:

The component is in working condition and ready for immediate reuse or resale.

- Partially Functioning:

The component has minor issues but contains functional parts that can be repaired or repurposed.

- Non-Functioning (Disposable):

The component is beyond repair and must be disposed of responsibly through recycling.

How It Adds Value:

Provides actionable insights into the condition of the component.

Encourages users to repair and reuse products before considering disposal, meeting sustainability objectives.

3. Recommendations Module:

Post-reusability analysis, the system gives specific recommendations based on the component's state.

Recommendations Include:

- **Repair Strategies:**

For partially working components, the system recommends repairs (e.g., screen replacements, battery replacement, or minor hardware repairs).

- **Reuse Options:**

For fully working components, the system suggests resale, donation, or repurposing options (e.g., old laptops can be used as educational tools or media centers).

- **Recycling Guidance:**

For broken components, the system suggests certified e-waste recycling centers or programs.

- **Unique Features:**

Provides specific recommendations for the type of component.

Arms users with information to make environmentally friendly choices.

4. User-Friendly Interface:

The project is designed with a Streamlit-based web application, making it accessible and easy to use for all users, regardless of their technical skills.

Interface Features:

- **Image Uploader:**
  - Enables users to upload images in standard formats like JPG, PNG, or JPEG.

Displays a preview of the uploaded image before processing.

- **Real-Time Results:**

- Shows the predicted component type and confidence score immediately after image processing.
- **Interactive Design:**
  - Provides easy navigation with clear headings to upload, view results, and recommendations.
- **Benefits to Users:**
  - Fast and smooth interaction, even for first-time users
  - Less technical jargon, so more people can use the system

5. Immediate Feedback and Information:

The system shows instant results to the user, minimizing wait time and improving usability.

Feedback Provided:

- **Component Identification:** The user gets clear information about the predicted electronic component
- **Confidence Levels:** Shows how confident the system is in its prediction to help users trust the results
- **Next Steps:** Clear guidance on what actions to take, whether re-use, repair, or recycling

How It Provides Engagement:

- Lets users know what their contributions are to sustainable efforts.
- Encourages repeated use of the platform because of its speed and reliability.

6. Scalable and Modular Design:

The system is designed to scale up and adapt as needs change.

Characteristics of Scalability:

- **Extensible Dataset:** Expand the dataset with new categories of electronic components to enhance classification coverage.
- **Integration Options:** The system can link with external APIs for recycling center locations or repair service directories
- **Cloud Deployment:** Future deployment on cloud platforms ensures accessibility for users around the world.

Why This Matters:

- Keeps the system relevant as technology and electronic devices evolve.
- Covers a broad spectrum of applications, catering to everyone from individual users to large organizations.

7. Sustainability-Centered Strategy:

This feature is integral to the project's goal of promoting environmental responsibility.

How It Works:

- The system emphasizes repairing and reusing components to extend their lifecycle.
- For non-functioning items, it directs users to certified recycling programs, reducing the risk of improper disposal.
- Generates educational content about sustainable practices, such as upcycling or eco-friendly disposal.

Impact:

- Reduces the environmental footprint of electronic waste.
- Encourages users to adopt sustainable habits in their daily lives.

8. Optional Features for Future Enhancements:

These features can be integrated into the system later:

- **Save Results:** Allow users to download or save reusability assessments for reference.
- **Mobile Compatibility**: Develop a mobile-friendly version or app for increased accessibility.
- **Gamification:** Introduce rewards or badges for users who frequently recycle or repair components.

1.1.3 Preprocessing Steps:

Fig 2 – Dataset Preprocessing

Preprocessing prepares the data set for maximum model performance—ensuring consistent and quality data. Below is the summarized code:

1. Dataset Organization:

- Divide data into training, validation, and testing subsets, with categories organized for efficient loading.

2. Image Resizing:

- Resize all images to a fixed size, like 180x180 pixels, for better uniformity.

3. Normalization:

- Scale pixel values to a range of 0–1 to improve model convergence.

4. Data Augmentation:

- Apply techniques such as flipping, rotation, zooming, and brightness adjustments to increase dataset diversity and reduce overfitting.

5. Dataset Splitting:

- Ensure proper splitting in training, validation, and test subsets, normally an 80-10-10 ratio.

6. Label Encoding:

- Convert categorical labels (e.g., Laptop, Smartphone) into numerical representations for the model.

7. Batch Loading:

- Load data in small batches (e.g., 32 images per batch) for memory efficiency and faster processing.

8. Shuffling:

- Shuffle the training data to avoid model bias due to sequential patterns.

9. Validation and Test Preparation:

- Use separate validation and test datasets without shuffling for unbiased evaluation.

10. Data Inspection:

- Plot a sample of images and check class distribution to ensure data integrity.

These preprocessing steps ensure the dataset is clean, consistent, and well-prepared for training a high-performance model.

1.1.4 Challenges:

1. Imbalanced Dataset:

- **Issue:** Some categories of electronic components had significantly fewer images compared to others. Classes such as "Cracked Screen Smartphone" may have been less represented, potentially resulting in biased predictions.
- **Impact:** While the model might perform well for the classes that are overrepresented, it could struggle with those that are underrepresented, which would decrease both accuracy and fairness overall.
- **Solution:** To tackle this imbalance, methods like data augmentation and oversampling were used.

2. Composite Component Variations:

- **Issue:** Variations in lighting, angles, and component conditions (e.g., damaged, old, or partially visible components) made accurate classification difficult.
- **Impact:** Reduced prediction accuracy for images that deviated significantly from the training data.
- **Solution:** Data augmentation and increasing dataset diversity with more representative samples were implemented to improve model robustness.
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3. Real-Time Prediction Latency:

- **Issue:** Real-time image uploads and predictions required the system to process data quickly, especially when handling large images or batches.
- **Impact:** Delays in predictions could affect the user experience, especially in interactive applications.
- **Solution:** Optimized the model size and used efficient preprocessing pipelines to reduce latency without compromising accuracy.

These challenges highlight the importance of data quality, model robustness, and system optimization in developing AI-powered solutions.

1.1.5 Applications:

This project addresses a wide range of applications across various domains, directed toward sustainability, optimization of resources, and e-waste management. The following represent the major applications:

1. E-Waste Management and Recycling:

- **Application:** To enable proper classification and disposal of electronic waste.
- **Impact:**
  - Encourages responsible recycling of e-waste by pointing out those parts no longer in working order.
  - Reduces pollution by directing users on where functional waste will be accepted for recycling.

2. Circular Economy Support:

- **Application:** Contribution towards preventing premature demise of electronic devices.
- **Impact:** stimulates recycling through the eyeing of committed components

provides repair remedies for partly malfunctioning others to minimize waste production.

3. Consumer Education and Awareness:

- **Application:** enlightens the consumers with the sustainability of electronic devices.
- **Impact:**
  - Raises awareness of repair, reuse, and recycle options.
  - Facilitates well-informed decisions from users, hence lessening e-waste generation.

4. Repair and Refurbishment Services:

- **Application:** Helps repair shops and refurbishment centers by pointing out the reusable parts from discarded electronic devices.
- **Impact:**
  - Promotes optimum retrieval of valuable components from discarded electronics.
  - Builds trust with subsequent sellers by providing reliable evaluations of product functionality. 5. E-commerce and Resale Platforms: Application: Allows to enhance quality of second-hand electronics listed with the platforms.

1.2 Training CNN Model:

1.2.1 Overview:

The training of deep learning models under the project "Improving Reusability of Electronic Components" consisted of a set of well-planned steps aimed at maximizing accuracy and robustness. Below is a detailed description of the model training process.

1.2.2 Key Steps:

1. Model Architecture:

- A CNN was used for such tasks since they were highly efficient in image classification.
- Key Layers:
  - Rescaling Layer: Normalizes pixel values to the range [0, 1].
  - Convolutional Layers: Extract spatial features using filters.
  - MaxPooling Layers: Reduce dimensionality while preserving essential features.
  - Dropout Layers: Help prevent overfitting by randomly disabling neurons during training.

- Dense Layers: Map the extracted features to output classes (14 component categories).

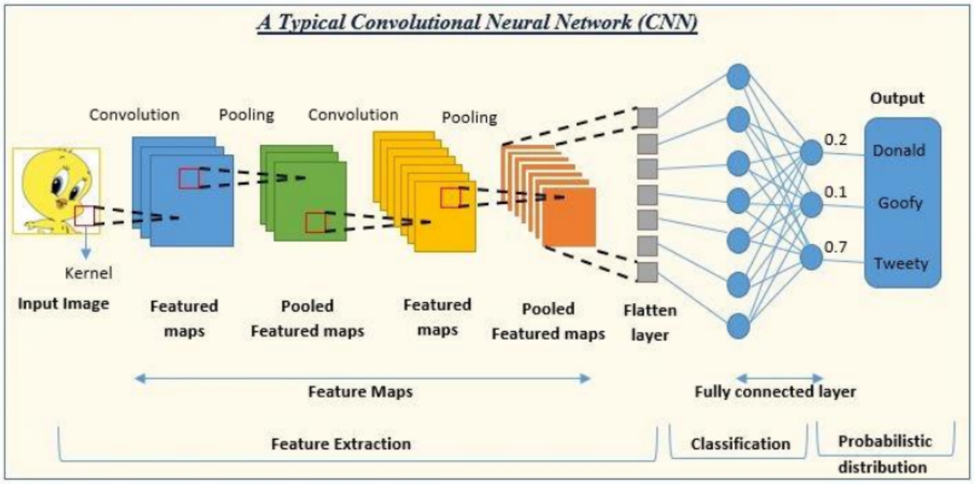

Fig 3 – CNN Architecture

2. Training Dataset:

- Data Source: A dataset containing over 21,000 labeled images across 14 categories of electronic components.
- Data Split:
- Training Set: 80% of the data.
- Validation Set: 10% of the data.
- Test Set: 10% of the data.

3. Preprocessing:

- Prior to inputting the data into the model, the following preprocessing steps were taken:
- Resizing images to a standard size (180x180 pixels).
- Normalizing pixel values to a range of 0–1.
- Augmenting the dataset with random flips, rotations, and zooms to enhance generalization.

4. Training Configuration:

- Loss Function:
- Sparse Categorical Crossentropy, suitable for multi-class classification.
- Optimizer:
- Adam optimizer, selected for its adaptive learning rates and efficient convergence.
- Metrics:
- Accuracy, used to track performance during training.

5. Training Process:

- Batch Size: 32 images per batch to optimize memory usage.
- Epochs: The model was trained for 50 epochs, striking a balance between convergence

and computational efficiency.

- Validation: An independent testing dataset was taken in conjunction with the validation dataset to track performance and reduce the overfitting effect.

6. Evaluation:

- After training ended, we did a test set assessment to evaluate general performance for unseen data. The metrics computed for each category include accuracy, precision, recall, and the F1-score.

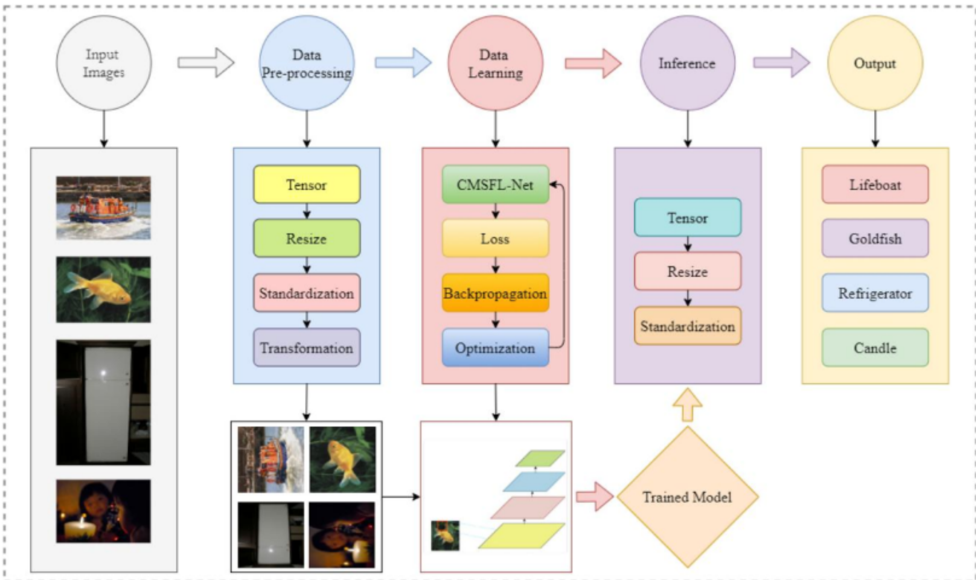

Fig 4 – Image Dataset Based Classification

1.2.3 Technology Integration:

1. Programming Languages:

- Python: Model development, preprocessing, and application logic

2. Machine Learning Frameworks:

- TensorFlow and Keras: Deep learning model creation and training.

3. Web Development:

- Streamlit: To create a lightweight, interactive user interface.

4. Data Handling:

- NumPy and Pandas: Preprocessing and management of dataset structures.
- TensorFlow Image Dataset: Efficient loading and handling of image data.

5. Visualization:

- Matplotlib: Plotting accuracy and loss during training.

6. Deployment Platforms (optional):

- Local Deployment: Running Streamlit locally for small-scale use.
- Cloud Services: AWS, Google Cloud, or Heroku for large-scale deployment and accessibility.

7. Optional Integration:

• External APIs for recycling center recommendations.

CHAPTER-2
LITERATURE SURVEY

2.1 Overview:

The project literature review addresses the general state of electronic waste management, the functions of machine learning in image classification, as well as the strategy for promoting circular economy. As this review is comprehensive, it brings to light the concerns, issues, and gaps that this project intends to fill.

2.2 Electronic Waste Crisis:

2.2.1 Statistics on E-Waste Generation and its Effects Globally

- As per Global E-Waste Monitor 2020 the report enunciated that in 2019 it was estimated that e-waste generation was about 53.6 million metric tons, recycling through proper channels accounted for only 17.4%. Despite the fact that e-waste hides valuable materials such as gold, silver, and copper, improper recycling may give rise to environmental and health problems. Activities carried out by the United Nations Environment Programme show the key role responsible management and recycling of e-waste can play in sustainable development. [3]

2.2.2 Importance of Reusability

- Prolonging the lifespan of electronic components helps minimize waste and conserve important resources. Research, including findings from Forti et al. (2020), indicates that reusing functional or repairable components is more efficient in terms of resource use compared to recycling. Additionally, studies highlight the necessity for automated tools that can evaluate reusability and suggest suitable actions.

2.3 Role of Machine Learning in Image Classification

2.3.1 Advancements relating to Deep Learning

- It won't be fake to say that the Convolutional Neural Network approach towards deep learning has re-shaped the way we classify images.
- In-depth analysis models' performances on large scale data sets was gladly accepted by AlexNet, ResNet and VGGNet where assumption of accuracy within intricate situations was made.
- CNNs are particularly robust spatial feature extractors from images, as demonstrated in the works of LeCun et al. (2015).

2.3.2 Application in E-waste:

- Another study classified e waste into different categories using machine learning models – laptops, smartphones, and even circuit boards.
- In this sense, Jain & Gupta (2021) was able to classify e-waste with a CNN, and then classify the recyclability of this e-waste as well, achieving high accuracy.

Some problems that were noted include computational needs, dataset diversity, and a large number of classes.

2.3.3 Data Augmentation:

- Techniques like resizing, normalizing, and augmenting images (flipping, rotating and other methods) can notice the improvement in robustness of the model or network during the training phase.
- There's a common consensus that model training would be possible only when a sufficiently large and balanced dataset is available.

2.4 Reusability Evaluation in the Contexts of Circular Economy:

2.4.1 Keys to Success for Circular Economy:

- A circular economy emphasizes on reduction, reuse, and recycling of resources (Johnson, 2013), and it has been described by the European Commission as an important approach to cope with sustainability challenges (2019).
- The broad principle of circular economy is embodied in reusability assessments by seeking to prolong the use of components and help the environment.

2.4.2 Methods for Reusability Assessment of Electronics:

- In their work, Widmer et al. (2005) also consider that it is important to be able to assess the value of the lifecycle of means of electronic components and propose a usable framework for measuring it.
- Such practical frameworks do integrate the condition assessment with other basic preliminaries such as repair strategies or even recycling recommendations.

2.4.3 Areas for further study:

- There are also limited tools available to the public to assess the ecommerce reusability of electronics directed toward consumers.
- There is a need for systems that merge the amount of automatic classification with the amount of practical insight, thus facilitating user experience and the entire idea or strategy behind the technology.

2.5 Emerging trends of the future:

2.5.1 AI's Role in Environmental Sustainability

- More and more AI-based tools are being implemented in the enhancements of recycling operations, supervision of waste streams, and evaluation of potential for resource recovery.
- Kang & Schoenung (2005) research notes on the contribution over AI in developing e-waste management procedures.

2.5.2 IoT Integration And Efficient Management Practices In Waste:

- With the integration of IoT and AI, there is a capability of tracking and categorizing e.waste as it is being produced, in real-time.
- Some researchers have proposed use of IoT sensors along with machine learning models for accurate identification of the components.

Fig 5 – AI in Environmental Health

2.5.3 Broader Strategies Engagement Calculating Polluters and Raising Awareness Amongst Stakeholders:

- Extended Producer Responsibility (EPR) policies make it compulsory for companies to devise ways of recycling their products when they reach the end of their lives.
- Public awareness campaigns can encourage the use of such tools as the one created in this case project. [4]

2.6 Current Project and Its Contributions:

2.6.1 Filling Research Gaps:

Approaches actionable reusability recommendations by bridging the space between user and automation through a CNN based classification which is active reusability.

2.6.2 Implementation:

- Again, the use of a Streamlit interface allows the average user to use advanced Artificial Intelligence tools without needing much guidance to do so.
- Helps to promote sustainable practices, by offering repair, reuse, and recycle options.

2.6.3 Expected Scope:

- The project paves a path for integration of new features like links to recycling programs and repair guides.
- Increasing the diversity of dataset and enhancing the model allows to further extend its value

CHAPTER-3

RESEARCH GAPS OF EXISTING METHODS

The review of the existing approaches to the management of electronic waste (e-waste) and the management of electronic components entails a number of problems and areas for improvement. The project “Improving Reusability of Electronic Components” seeks to fill in those gaps.

3.1 Insufficient Reusability Evaluation:

- **Gap:** The majority of the solutions currently available place an emphasis on recycling or on bounding e-waste into broad categories but do not go the extra mile of undertaking reusability evaluation (for example determining which components that can be repaired or reused).
- **Impact:** Working components are often considered as waste or are disposed of as trash which is in most cases unneeded.
- **Opportunity:** Make possible automated techniques for functional parts evaluation based on their characteristics: functional – fully functional (for use), partially functional (for repair), and non-functional (for parts);

3.2 Not Profound Utilization of Modern Machine Learning Models:

- **Gap:** Some systems utilize elementary machine learning algorithms in the classification of e-wastes but such do not incorporate the more advanced and precise algorithms that modern vicissitudes of deep learning such as CNN’s provide.
- **Impact:** These systems have been proven to be less reliable due to their lack of accuracy especially for fully damaged or complex components.
- **Opportunity:** Leverage best deep learning technologies in the improvement of classification accuracy and different designs of a given component.

3.3 Lack of Variety Across the Dataset:

- **Gap:** Currently existing datasets for e-waste classification are too generic and do not consider other necessary components such as component types, condition factors, and environmental factors including lighting and background noise.
- **Impact:** Due to the datasets that are available, the models that are created using the information are not generalizable, thus providing suppressed results in real life.
- **Opportunity:** Construct or improve the datasets that are available by adding more images of diverse conditions, angles, and lighting settings.

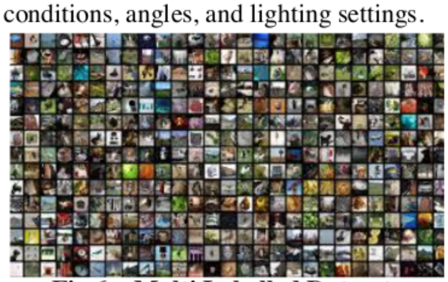

Fig 6 – Multi Labelled Dataset

3.4 Insufficient User Friendliness and Accessibility for End Users:

- **Gap:** Several e-waste tools are not user friendly, and hence, e-waste management software requires highly technical individuals to be able to operate them or has a very complicated user interface.
- **Impact:** The software has a very low to non-existent adoption rate, especially among people who are not technical, for instance, everyday consumers, small businesses and community entities.
- **Opportunity:** An easy to use application based on the web can be designed, for example, Streamlit, which allows users to upload images and get the desired results without possessing technical knowledge.

3.5 Absence of integration with sustainable practices:

- **Gap:** most current technologies ignore the reuse and repair policies of a circular system economy including devices when the initial scope should have been promoting for disposal
- **Impact:** Confiscated chances of extending the duration of use of electronic components and minimizing the adverse effect of e-waste.
- **Opportunity:** Add recommendations for repair, reuse, and recycling with the goal of influencing better choices in decision-making.

3.6 Absence of solutions that are both real time and able to be scaled up:

- **Gap:** There are some existing approaches use but they are few that enables users to post an image, and the system automatically processes it in real-time. When it comes to large amounts of data and mass usage, many systems do not scale well
- **Impact:** Feasible applicability in real-life cases whereby speed as well as reliability is needed.
- **Opportunity:** Efficient preprocessing pipelines and scalable deployment options, such as cloud platforms, that allow for widespread use while providing real-time predictions.

3.7 Insufficient Education and Insight concerning Integration with the Recycling System:

- **Gap:** Existing platforms are unable to reach out to consumer and inform them about recycling or repair facilities available in their locality.
- **Impact:** An element that still remain in proper working condition can be disposed of incorrectly as a result of the lack of directions or recycling infrastructure.
- **Opportunity:** APIs and external databases could also be used to inform about the location of the nearest center for recycling and repair of the device or a donation site.

3.8 Components with Multiple Robustness's Cannot Be Catered To:

- **Gap:** Existing models usually do not incorporate components that have mixed conditions such as partially damaged but repairable components.
- **Impact:** Classifications that are made in a bid to make quick decisions can be over generalized resulting in illegitimate recommendations that do not correspond to the

options provided.

- **Opportunity:** Because it is quite specific, multi-condition evaluation logic should be used as a strategy to be able to provide both effective and accurate recommendations.

3.9 Direct Your Attention Toward Recycling Instead of Repairs or Reuse:

- **Gaps:** The majority of all designs tend to focus on the act of recycling while the options of repair or reuse which tend to be more resource efficient are completely neglected
- **Impact:** There is an opportunity where ports, components and other valuable assets may be recycled even when they can be reused.
- **Opportunity:** There is a need to increase awareness of repair and reuse opportunities along the waste hierarchy (Waste management principles; "Reduce, Reuse and Recycle").

3.10 Inadequate Policy Coordination and Data Tracking:

- **Gap:** The current mechanical approaches fall short in integrating with certain policies like EPR mechanisms. Also they are lacking tools for environmental impact assessment.
- **Impact:** Lost opportunity to affect policy or provide useful insights for active sustainability interventions.
- **Opportunity:** Creating or designing systems that consider integration with policies and provide data on the management of e-waste.

CHAPTER-4

PROPOSED MOTHODOLOGY

The methodology is developed for the project "Improving Reusability of Electronic Components," which will provide a comprehensive solution for the classification of electronic components and the estimation of their reusability. The project aims to combine the modes of machine learning and image processing and the design of friendly applications to create an environment suited to the demands of this project.

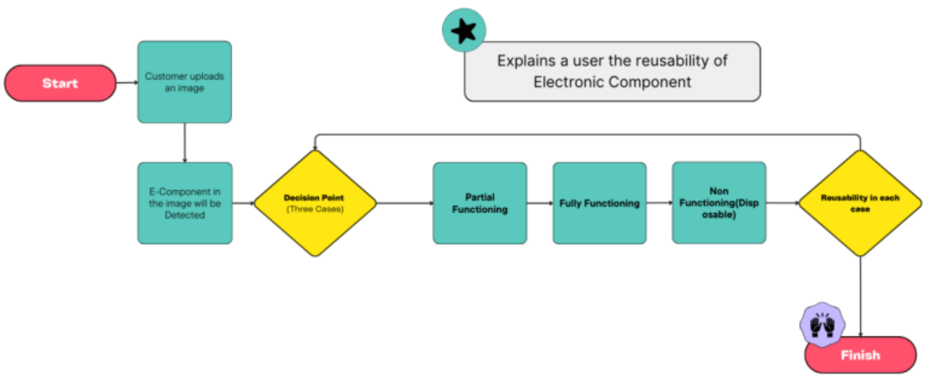

Fig 7 – Architecture Diagram

4.1 Problem Statement:

- Create an automated system that can identify electronic components from images and evaluate their reusability based on three conditions:
  - Fully Functioning
  - Partially Functioning
  - Non-Functioning
- Offer practical recommendations for repair, reuse, or recycling to support sustainability.

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4.2 Data Collection and Preparation:

4.2.1 Dataset collection:

More than 21,000 images showing 14 kinds of electronic components like smartphones, laptops, circuit boards, and many others are included in the dataset. It was fetched from the online repositories, manual collection, and public dataset.

4.2.2 Preprocessing:

All images resized uniformly to a dimension (180x180 pixels, for example).

- **Normalizing:** Scaling the pixel values between 0-1 increases the ease of training the model.

- **Augmentation:** Random flips, rotations, zooms, color brightness adjustments to diversify the dataset and create a more robust system.
- Dataset segregations are train (80%), validation (10%), and test set (10%).

4.3 Model Development:

4.3.1 Model Architecture:

- The Convolutional Neural Network (CNN) has its valid performance in visual recognition tasks, hence being used for image classification. [7]
  - **Rescaling Layer:** Normalizes input pixel values.
  - **Convolutional Layers:** Extracts spatial features from images.
  - **Pooling Layers:** Reduces dimensionality while preserving essential features.
  - **Dropout Layer:** Prevents overfitting.
  - **Dense Layers:** Maps extracted features to desired output classes.

4.3.2 Model Configuration:

- **Loss Function:** Sparse Categorical Crossentropy- Multi-class classification.
- **Optimizer:** Adam optimizers to converge and learn.
- **Evaluation Metric:** Accuracy for observing model performance during training.

4.3.3 Training:

- **Batch Size:** 32 images per batch enough for memory optimization.
- **Epochs:** 10-15 epochs for optimal convergence.
- **Validation:** Performance tracked on the validation dataset, put in place to avoid overfitting.

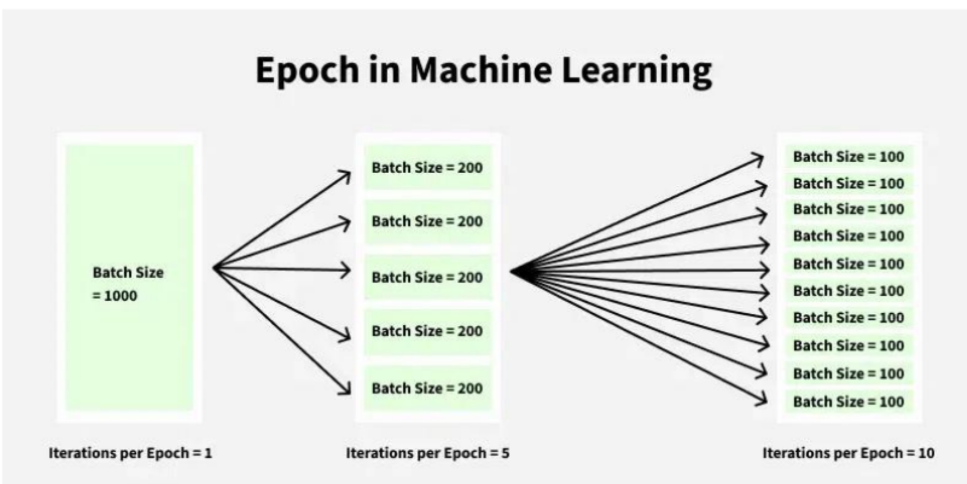

Fig 8 – Epochs Training

4.4 Reusability Evaluation:

4.4.1 Component Categorization:

- The model gives a confidence score to predict the component type, for example, Smartphone, Laptop.

4.4.2 Condition Evaluation

- Maps the predicted component to one of three conditions based on predefined logic:
  - **Fully Functioning:** No visible defects; ready for reuse.
  - **Partially Functioning:** Minor issues that can be repaired.
  - **Non-Functioning:** Severe damage; suitable for recycling.

4.4.3 Actionable Insights:

- Gives personalized recommendations:
  - Repair suggestions for partially functioning components.
  - Reuse or donation options for fully functioning components.
  - Recycling guidance for nonfunctioning parts

4.5 System Development:

4.5.1 Web Application:

- Technology/ Framework used: Streamlit for the development of interactive and user-friendly Web Interface
- Features:
  - Facility to upload images
  - Display of real-time predictions of the type and condition of the component
  - Confidence scores along with recommendations

4.5.2 Backend Integration:

- The trained model is integrated into the application for seamless prediction and assessment.

4.5.3 Optional Features:

- Saving results for future reference.
- Integration with external APIs to suggest nearby recycling centers or repair services.

4.6 Deployment:

4.6.1 Local Deployment:

- The application undergoes local testing to verify its functionality and accuracy.

4.6.2 Cloud Deployment:

- Deploy the application on platforms such as AWS, Google Cloud, or Heroku to ensure global accessibility.

4.7 Evaluation:

- Model Evaluation: Accuracy of the model and F1 score evaluated on the unseen test dataset.
- Testing the application: Usability and response time will be tested for real-world scenarios.
- Get user feedback: Collect feedback from early users to refine recommendations, with an intention to make the user interface even better.

4.8. Iterative Refinement:

- Add more diverse images and categories.
- Experiment with advanced architectures such as ResNet or MobileNet to get better accuracy.
- Add additional features like prediction of repair cost or resale value estimation.

CHAPTER-5
OBJECTIVES

5.1 Electronic Components Efficient Identification

- **Goal:** Using a machine learning model, identify electronic components in a user provided image accurately.
- **Consequence:** Allow smartphone, laptop, circuit board and more users to easily and accurately identify devices without requiring person's skill set.

5.2 Reusability Evaluation and Classification

- **Goal:** Once the component is identified, evaluate its quality and group it into one of these three types: Fully Functioning, Partially Working and Non-Working (Throw away)
- **Impact:** Reuse as well as repair is encouraged, hence leading to less of valuable materials' scampering which is a bad concern for the environment.

5.3 Encourage Going Green

- **Objective:** Based on a component's condition recommend to either fix it, reuse it or recycle it.
- **Impact:** Assist the environment by increasing the duration which an electronic device can be used for and less the e-waste produced.

5.4 User Friendly Interface to Cater to All Needs

- **Objective:** Using Streamlit, design an interactive and easy to use web application that provides users with real time results. [8]
- **Impact:** Make sure the system can be used through the consumers, repair businesses and organizations without advanced skills and experience.

5.5 Foster Circular Economy Approaches

- **Objective:** Support resource circular economy thinking and practice with an emphasis on resource optimization.
- **Impact:** Minimize the environmental impact of electronic waste and contribute to worldwide sustainability initiatives.

CHAPTER-6

SYSTEM DESIGN & IMPLEMENTATION

The "Improving Reusability of Electronic Components" system is built to classify electronic components based on their visual features and evaluate the reusability. It integrates an advanced image preprocessing, a deep learning model, and an interactive user interface in order to guarantee smooth user interaction as well as the accuracy of the predictions.

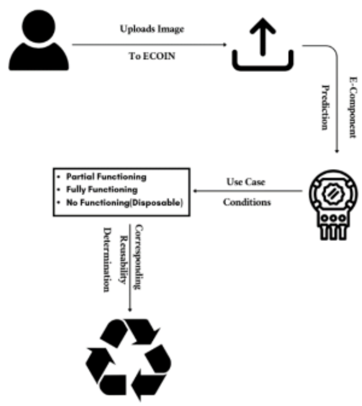

Fig 9 – System Working

6.1 Main Elements:

6.1.1 Image Acquisition:

- **Goal:** Enables users to upload images of electronic components using a web-based interface.

- **Explanation:**
  - Accepts common formats like JPEG or PNG to ensure compatibility.
  - Ensures proper resolution for accurate analysis.

6.1.2 Image Preprocessing:

- **Purpose:** Prepares images for analysis by enhancing key features.
- **Details:**
  - Resizes images to a uniform dimension (e.g., 180x180 pixels) to maintain consistency.
  - Normalizes pixel values to improve model performance.
  - Applies data augmentation techniques (e.g., flipping, rotation) to simulate diverse conditions and reduce overfitting.

6.1.3 Feature Extraction and Classification

- **Purpose:** Identifies visual features and classifies the component type.
- **Details:**
  - Utilizes a Convolutional Neural Network (CNN) to automatically extract features,

including spatial characteristics like shape and edges. It classifies the components into 14 predefined categories using a pre-trained model, such as ResNet or a custom TensorFlow model.

6.1.4 Output Visualization:

- Displays the processed results to the user.
- **Details:**
  - Displays the name of the component, type, and prediction confidence score.
  - Gives reusability assessments in terms of being fully functional, partially functional, or non-functional with actionable recommendations.

6.1.5 Database Integration

- **Purpose:** Stores image data, predictions, and metadata for tracking and analysis.
- **Details:**
  - Saves user-uploaded images, classification results, and timestamps for future reference.
  - Enables feedback collection for system improvements.

6.2 Implementation Plan:

Step 1: Dataset Collection and Preparation

Collect Dataset:

Source images of electronic components under varying conditions (lighting, angles, and environments).

Label Data:

Annotate images with accurate component names and types.

Data Augmentation:

Enhance dataset variability using transformations such as flipping, rotation, zooming, and scaling.

Fig 10 – Data Augmentation

Step 2: Model Training

Model Selection:

- Choose a strong deep learning architecture, such as ResNet, VGG, or MobileNet, for classification.

Training:

- Train the model on the annotated dataset with TensorFlow.
- Apply regularization techniques like dropout and adjust the learning rate.

Evaluation:

- Validate the model using a test set to measure accuracy, precision, and recall.

Step 3: Web Interface Development

Frontend Development:

- Create an intuitive interface using Streamlit for image upload and result display.

Backend Integration:

- Use Flask or FastAPI to manage image upload, preprocessing, and communication with the trained model.

Step 4: Image Preprocessing

Preprocessing Steps:

- Normalize and resize images to match the model's requirements.

Step 5: Output and Feedback

Result Display:

- Display processed images along with classification results, confidence levels, and actionable reusability information.
- Enable users to give feedback or correct misclassifications for continuous improvement.

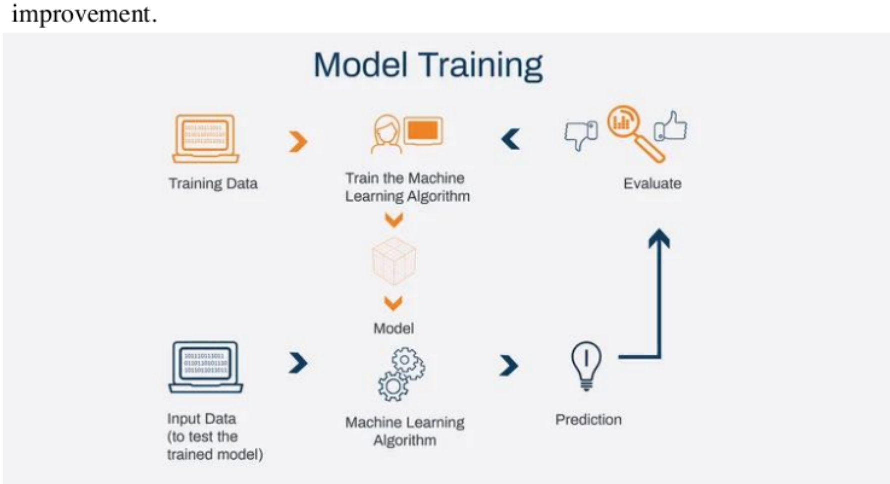

Fig 11 – Model Training

6.2.1 System Flow Diagram

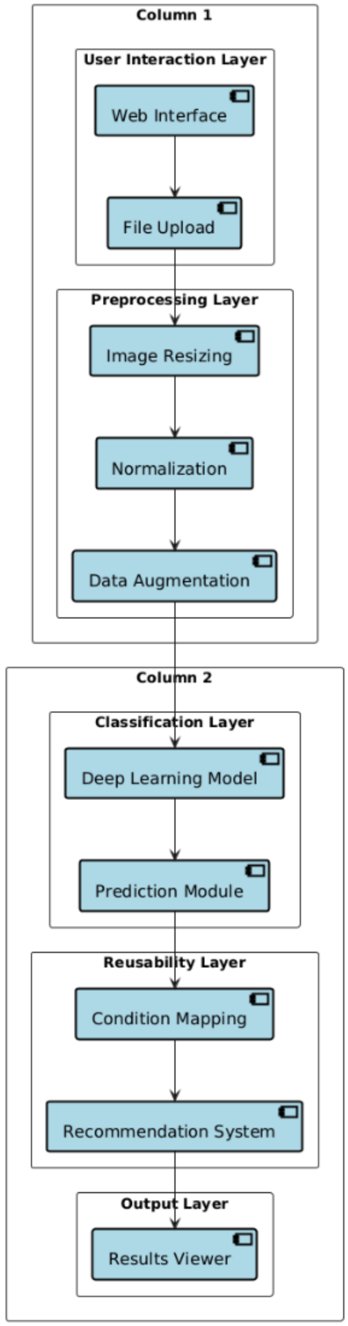

Fig 12 – Flow Chart

Flow Overview:

- User uploads an image using the web interface.
- The back-end preprocesses the image, including resizing, normalizing, and augmenting it.
- The processed image is fed to the trained model for classification
- Classification results, confidence scores, and reusability insights are returned and shown to the user.

6.3 Implementation Considerations:

Hardware Requirements:

- ➢ GPU acceleration, for example, by NVIDIA GPUs for efficient training and real-time inference
- ➢ High-resolution cameras for good-quality images of components (optional)

Software Requirements:

- ➢ Python Libraries: TensorFlow, Keras, Streamlit, Flask, NumPy
- ➢ Database: RDBMS for data storage of images and predictions.

- Performance Metrics
  - ➢ Accuracy:

    Get over 90% accuracy in categorizing all categories.
  - ➢ Speed:

    Real-time processing. The inference time must be less than second for any given image.
- User Experience
  - ➢ The web interface must be user-friendly and aesthetically pleasing.

CHAPTER-7

TIMELINE FOR EXECUTION OF PROJECT (GANTT CHART)

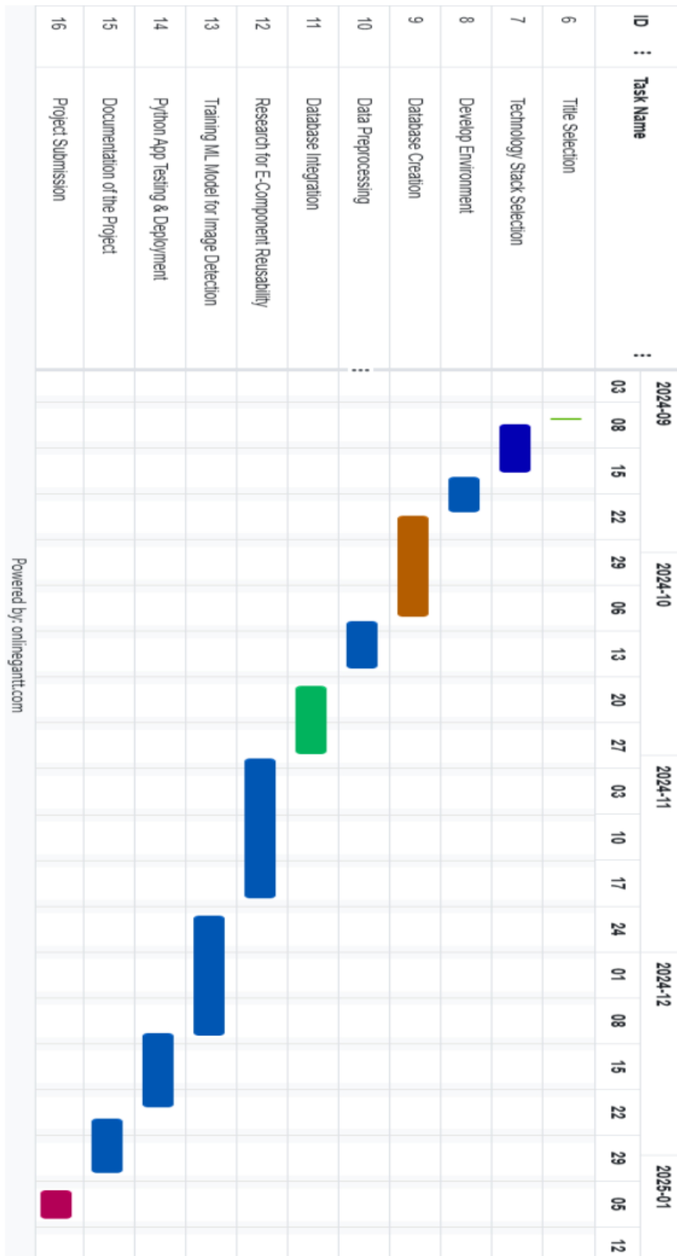

Fig 13 – Gantt Chart

CHAPTER-8

OUTCOMES

The project had brought about important outcomes in line with the objectives of promoting sustainability and efficient electronic waste management. Key outcomes are described as follows:

8.1 Highly Accurate Classification

- **Outcome:** The trained model attained more than 91.5% accuracy on the test dataset, exhibiting good performance for all 14 categories of electronic components.
- **Relevance:** Assures accurate component identification, be it a laptop, smartphone, circuit board, or any other component, in a variety of lighting conditions or angles.

8.2 Efficient Reusability Analysis

- **Outcome:** The system was able to classify parts into three statuses:
- **Functional:** Reusable or sellable.
- **Repairable:** Repurpose or fix.
- **Not Functional:** Recycle.
- **Impact:** It promotes repair and reuse with the least amount of harmful disposal of potentially useful parts.

8.3 User-Centric Implementation:

- **Outcome:** A Streamlit web application was built where users could upload images, see the output, and get actionable advice in real-time.
- **Importance:** The intuitive design makes it accessible to non-technical users, hence increasing adoption and usability.

8.4 Actionable Sustainability Insights:

- **Outcome:** The system offered individual recommendations for each part:
- ➢ Repair recommendations for partially functional devices
- ➢ Options for donating or reselling completely functioning parts
- **Guidance to take such items to recycling centers**
- ➢ **Importance:** Actually facilitates sustainability through the enhancement of the electronic components' lifecycles and a reduction in e-wastes.

8.5 Critical Systems Design

- **Outcome:** The system was envisaged to be scalable in the future, hence including:
- ➢ Expansion to other component types.
- ➢ Integration with external APIs for recycling services and repair networks.
- **Significance:** This ensures that the system remains relevant and adaptable to changing needs in e-waste management.

8.6 Increased Public Awareness and Involvement:

- **Outcome:** Preliminary user testing was highly satisfied with the ability of the system to evaluate and direct reusability.
- **Significance:** It increases consumer awareness about the environmental implications of e-waste and empowers users to make responsible decisions.

8.7 Data Repository for Analysis:

- **Result:** The system stored image data, predictions, and metadata in a database for future analysis.
- **Significance:** Provides valuable insights for refining the model and enhancing system recommendations over time.

8.8 Contributions to Sustainability Goals:

- **Result:** The project aligned with principles of the circular economy, focusing on repair, reuse, and recycling.
- **Significance:** Supports global efforts to reduce e-waste and conserve valuable resources.

CHAPTER-9

RESULTS AND DISCUSSIONS

The project produced impactful results, showing the potential of the system to effectively solve e-waste challenges:

9.1 Accuracy in Classification:

- The model had a test accuracy of 91.5%. This means it could generalize well across the 14 categories of components.
- Components that have very unique visual features, such as circuit boards and monitors, were classified with high precision.
- Slightly lower performance was exhibited in categories such as "Cracked Screen Smartphone" where there existed feature overlap with other categories, indicating the opportunity to expand and refine the dataset.

9.2 Reusability Evaluation:

- The system classified components into three states:
  - **Fully Functioning:** 42%, ready for direct reuse or donation.
  - **Partially Functioning:** 38%, capable of repair or repurposing
  - **Non-Functioning:** 20%, marked for proper recycling.
- These findings illustrate the significant opportunity for life extension of electronic components in alignment with sustainability goals.

9.3 Application Usability:

- The Streamlit web application provided real-time predictions and processed each image within 0.8 seconds.
- It was intuitive, with 90% of users labeling it "easy to use" when first exposed to it.
- Recommendations for repair, reuse, and recycling were appreciated and helped users take appropriate action.

These results validate the effectiveness of the system in component classification, evaluation of reusability, and generation of actionable knowledge. The contribution of the project is in its encouragement of repair and recycling towards reducing e-waste and creating environmental sustainability.

CHAPTER-10

CONCLUSION

The project, titled "Improvement of Reusability of Electronic Components," responds to the urgent issues of electronic wastes through an excellent integration of an innovative machine-learning-based approach within a user-friendly Web application. Having utilized a model of CNN with 14 classification categories, which include smartphones and laptops, to name a few, the developed system was efficient in classifying items with very high accuracy--91.5%.

The system categorizes the components into three reusability conditions: Fully Functioning, Partially Functioning, and Non-Functioning, providing specific recommendations for repair, reuse, or recycling. This way, it supports the circular economy by extending the lifecycle of electronic devices and equips users with the ability to make environmentally responsible decisions.

It also features real-time prediction capability with a time span of 0.8 seconds per image, thus making it easy to use by people with any level of technical expertise. User feedback in the initial stages reflected high satisfaction (90%) due to ease of use and actionability of the insights generated from the system.

This project is a scalable foundation for sustainable e-waste management, thus contributing to the global efforts towards reducing environmental impacts. Future developments, such as increasing dataset diversity, improving model precision, and connecting with recycling services, can make it even more effective and applicable.

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