Improving Reusability of Electronic Components

1st D JOY
Student
CST DevOps(of Aff.)
Presidency University (of Aff.) Bengaluru, India
dibbagalla.20211cdv0066@presidencyuniversity.in

2nd M S YESHWANTH
Student
CST DevOps(of Aff.)
Presidency University (of Aff.) Bengaluru, India
morubagal.20211cdv0039@presidencyuniversity.in

3rd K SNEHITH REDDY
Student
CST DevOps(of Aff.)
Presidency University (of Aff.) Bengaluru, India
kolli.20211cdv0006@presidencyuniversity.in

4th A VIGNESH RAJU
Student
CST DevOps(of Aff.)
Presidency University (of Aff.) Bengaluru, India
arava.20211cdv0005@presidencyuniversity.in

5th K BHARGAV TEJA
Student
CST DevOps(of Aff.)
Presidency University (of Aff.) Bengaluru, India
kallimekala.20211cdv0067@presidencyuniversity.in

6th Mr SHANKAR J
Assistant Proffesor
School of CSE
Presidency University (of Aff.) Bengaluru, India
shankar.j@presidencyuniversity.in

I. ABSTRACT

The project **"Improving Reusability of Electronic Components"** deals with the ever-increasing concern for electronic waste, which calls for a need for sustainability in terms of electronic components' disposal and repurposing. Electronic devices have seen massive growth due to technological advancement and are increasingly used in every corner of the globe, thereby turning into an immense environmental issue called e-waste. Based on the focus on research and development, this project establishes a robust system that shall estimate, classify, and strengthen the reusable potential of e-components, majorly focusing on laptops, using techniques of artificial intelligence and machine learning.

The prediction model classified the condition of the various e-components into either fully working or non-functioning units which fall within the disposable category. A predicted category aided by the condition of a particular component guides the decision-making process to reuse, repair, recycle, or dispose of it. It actually presents a two-condition approach by giving actionable output on whether or not the device is fully functioning or non-functional. For functioning devices, it recommends possible fixes or upgrades and thereby extends the device's useful life. The system identifies components to be recycled for non-functional devices or states whether they can be disposed of as e-waste.

Using automated classification and condition specific guidelines, the project aims to reduce e-waste, reduce environmental impact and prolong the lifespan of e-components. As a whole, the system seeks to promote sustainable usage, definitively achieving the reuse and recycling of valuable e-waste materials, making the electronics industry a greener one.

II. INTRODUCTION

The exponential increase in electronic waste (e-waste) is globally becoming a dire environmental challenge in today's technology-oriented society. Poor disposal of electronic devices invariably results in loss of valuable resources and environmental destruction. The project "Improving Reusability of Electronic Components" offers an innovative solution to this problem with machine learning and modern web-based applications for the sustainability of proper e-waste.

It focuses on a user-friendly application that allows the uploading of images of electronic components. The system uses a deep learning classification model trained on over 21,000 images to identify the electronic component and evaluate its reusability criteria under three conditions:

- Partially Functioning-Components that can be repaired or repurposed.
- Fully Functioning-Components that can be directly reused or donated.
- Not Functioning (Disposable)-Components that must be properly recycled or disposed of.

TensorFlow and a diverse dataset are used to build the model to identify the components with other common electronics. The model gives relatively high accuracy in identifying components like laptops, smartphones, and circuit boards. The project takes this classification feature into the Streamlit web application to give feedback on component reusability and sustainability.

By simplifying the auditing of e-waste and making personalized recommendations for repair, reuse, or recycling, this project aims to curb environmental damage and encourage responsible consumer behaviour. It builds a bridge between technological development and Greenness, offering a scalable and impactful solution to a global issue.

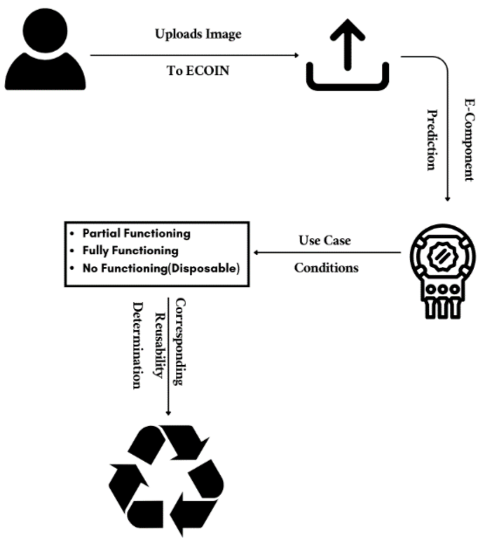


Fig.1 Use Case Diagram

This Use Case Diagram shows the interaction between the user and the system. It contains a step-by-step explanation as to how the process works:

1. User Interaction:

The interaction commences with the user uploading an image of an electronic component through the Streamlit application.

The system processes the image and makes a prediction about the type of component that appears on the image using the trained deep learning model.

2. System Processing:

Once the component is identified, the system checks for its reusability.

Here, this means the differentiating of the components into partially functioning, fully functioning, or not functioning.

3. Recommendations:

Depending on the reusability status, the system recommends repair options, donation possibilities, or authorized e-waste recycling centres.

4. Optional Use Cases:

Save Results: Users may save or download the assessment results for further reference.

Connecting to Recycling Service Providers: For any non-functioning components, the system may check external databases or APIs for suggestions for recycling centres nearby.

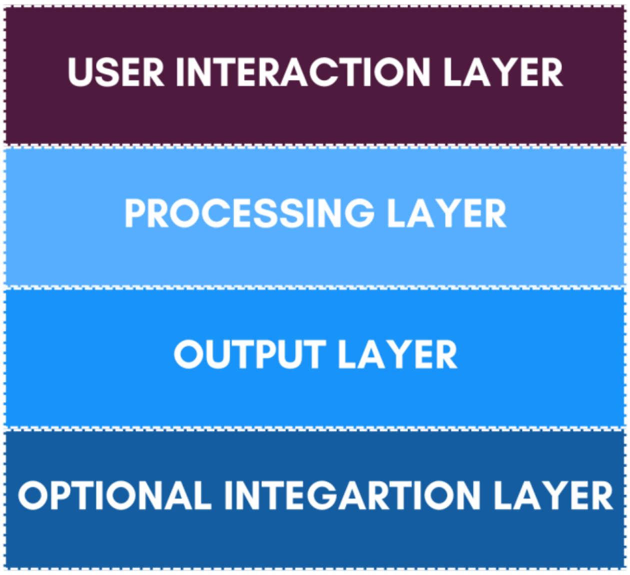


Fig.2 Architecture Diagram

Architecture Diagram The layers included are as follows:

1. User Interaction Layer:

- Streamlit app to upload images and view results

2. Processing Layer

- Image pre-processing and prediction using the trained model.
- Logic for decision making about reusability categorization

3. Output Layer

- Displays type of component, condition as fully working, partially working, or non-functioning, and recommendations

4. Optional Integration Layer

- APIs for recycling center suggestions
- Data storage for saving user results.

Architecture Components

1. Frontend (User Interface):

- Streamlit Application: It is a web-based interface that allows users to upload images and view results.
- Features: Image uploader, display for prediction results, and recommendations for reusability.

2. Backend (Processing and Logic):

Trained Deep Learning Model:

- Built using TensorFlow and Keras.
- It is responsible for image classification and predicting the electronic component.

Reusability Decision Logic:

- Maps the predicted category to predefined reusability conditions and recommendations.
- Example: Non-functional -> Fix recommendations; Functional -> Reuse or give away; Not working -> Recycle or throw away.

Data Storage:

- Stores model data, training outcomes, and optional user logs (e.g., uploaded images or results).

Model Training and Prediction:

- Dataset: Over 21,000 images classified into different electronic components.
- Model Pipeline:
  - ➢ Image pre-processing (resize, normalize).
  - ➢ Model architecture (Convolutional Neural Network - CNN).
  - ➢ Training and validation phases.
- Prediction:
  - ➢ Softmax activation returns the probabilities for each category.
  - ➢ The component with the highest probability is chosen.

Optional Services:

- Recommendation System:
  - ➢ Offer repair or recycling advice depending on the condition and type of the component.
- Integrate with Recycling Centres:
  - ➢ Provides nearby recycling facilities through APIs or external data sources.

Deployment:

- Local Deployment: Runs on the user's machine for small-scale testing.
- Cloud Deployment (Optional): Enables scalability and accessibility for a larger audience.

III. LITERATURE REVIEW

It covers existing literature pertaining to electronic waste management, classification systems based on machine learning and AI's application to sustainable practices. Here are the main themes and takeaways from the review:

1. Electronic Waste Management:

E-waste is now regarded as one of the world's most rapidly increasing volumes of waste, with grave consequences for the environment and human health.

- Statistics and Challenges:
  - ➢ The Global E-Waste Monitor estimated that 53.6 million metric tons of e-waste were produced globally in 2019, and only 17.4% was recorded as collected and recycled.
  - ➢ When not disposed of properly, e-waste results in a waste of resources and toxic pollution, making it an emerging remadation class on bioaccumulation.
- Main points:
  - ➢ Reuse and Recycle: An extension of lifespan is needed for electronic components through reuse, repairs, and recycling.
  - ➢ Consumer Education: Consumers do not have adequate knowledge on the disposal of e-waste, posing one key obstacle to waste management.
  - ➢ Gaps in Research:AI and automation are applied very less to assess e-waste in real-time.
  - ➢ No user-friendly application is available that can help the consumers in finding

electronic components and then managing them.

2. Machine Learning in Image Classification:

Machine learning and CNNs have transformed the concept of image classification.

- Applications of Machine Learning in E-Waste Classification:
  - The researchers have employed CNN in identifying various types of e-waste, for example, mobile handsets, laptop, and circuit board among others.
  - Results from studies reveal that machine learning can accurately determine component types even when complex visual differences exist.
- Improvement in Image Classification:
  - Deep Learning Models: Recent approaches like ResNet, VGGNet, and MobileNet which achieve high accuracy in classification.
  - Dataset Preparation: Preprocessing, augmentation, and large-scale datasets guarantee robust model performance
- Challenges:
  - Imbalanced datasets, with some categories not being well-represented, can negatively affect classification accuracy.
  - Training deep learning models can be very computationally intensive.

3. Reusability and Circular Economy:

A circular economy is, in essence, an economic system that aims to maintain the use of scarce resources for as long as possible through maximizing the recovering and regenerating of products and materials, with the minimum possible waste and energy use attached.

- Reusability Evaluation:

Classification of electronic components by functionality

  - Fully Functional: Can be used directly or resold.
  - Partially Functional: Can be repaired or repurposed.
  - Non-Functional: Needs recycling or safe disposal.
- Technology Implementation:
  - AI integration in component condition assessment enables accurate and efficient decision-making.
  - Automation can scale and be more accurate than human inspection.

4. Existing Solutions and Gaps

- Applications and Tools:
  - Some existing e-waste management tools provide general recycling information but do not personalize or offer component-specific information.
  - Tools like computer vision identifying the nature of wastes, have been developed though these are not widely used among the consumers
- Constraints in the Current Solutions
  - Accessibility and usability for non-technical people is restricted
  - No available integrated platform that combines classification, reusability evaluation, and actionable recommendations

5. AI and IoT Framework for Sustainable E-waste Management

- Research limitations arising from IoT and AI:
  - IoT and AI sensors are contributing to an "intelligent" system in monitoring and managing e-waste.
  - Real-time information from IoT sensors can be integrated to enhance tracking and categorization of e-waste.
- Policy and Education:
  - Many countries have implemented EPR policies that impose responsibility on manufacturers for recycling used products at their end-of-life.
  - Public education programs focus on promoting the idea of recycling e-waste, but penetration is very poor without technological integration.

6. Relevance to the Current Project:

This project rests on the following findings from literature:

1. AI for E-Waste Management: Using large datasets to improve the accuracy for classifying electronics using CNN

2. Reusability Assessment: Analysis of the reusability of components so that the currently available solutions might be filled out.
3. User Centric Designing: Streamlit-based interface usability and accessibility for any non-technical end-user
4. Actionable Recommendations to Reuse/Repair/Recycle: There is a technology-sustainability divide, and including recommendations for reuse or repair or recyclability bridges such a gap at the end.

The literature review therefore points to this potential and addresses the rapidly arising e-waste problem with this combination of using machine learning within sustainability practices. This project fulfills all of the above deficiencies and will address the growing and global need while aligning well with the general vision of a circular economy and proper and responsible management of e-wastes.

IV. METHODOLOGY

The methodology for the project "Improving Reusability of Electronic Components" explained step-by-step approaches to system design, development, and deployment. Here, machine learning, data preprocessing, system development, and user interaction are systematically put together. Below is the detailed methodology:

1. Problem Identification

- Objective: Develop a system to address the issue of increasing e-waste, by analyzing the reusability of electronic components.
- Scope: To develop a system that will perform such tasks:
  - Classify electronic components from images uploaded.
  - The reusability condition for the item (fully working, partially working, or not working).
  - Recommendations for reuse, repair, or recycling.

2. Data Collection and Preparation

2.1 Dataset Collection

- Dataset Source. 21,000+ annotated images of electronic devices such as laptops, smartphones, circuit boards and washing machines.
- Categories:
  - Ceiling Fan
  - CPU
  - Circuit Board
  - Computer Keyboard
  - Smartphone, etc.

2.2 Data Preprocessing

- Crop all input images to a uniform size, such as a 180 × 180 pixel image, to maintain uniformity.
- Normalization: Normalize the pixel values from 0–1 which is helpful for improving the performance of the model.
- Splitting: Split the dataset into:
  - Training Set (80%)
  - Validation Set (10%)
  - Testing Set (10%)

3. Model Development

3.1 Model Selection

- Framework: TensorFlow and Keras to develop a CNN.
- Architecture:
  - Input Layer: Rescaling to normalize pixel values.
  - Convolutional Layers: Extract spatial features.
  - MaxPooling Layers: Reduce dimensionality and computation.
  - Dropout Layers: Prevent overfitting.
  - Dense Layers: Map features to electronic component categories.

3.2 Training the Model

- Optimizer: Adam optimizer for efficient gradient descent.
- Loss Function: Sparse Categorical Crossentropy for multi-class classification.
- Metrics: Accuracy for evaluating model performance.
- Training Parameters:
  - Epochs: 10
  - Batch Size: 32

3.3 Evaluation

- Evaluate the model using the validation and testing datasets.
- Metrics:

- ➢ Accuracy
- ➢ Precision and recall for individual categories (optional).

4. System Design and Development

4.1 Web Application Development

• Framework: Streamlit to create an interactive web interface.

• Features:

- ➢ Image Upload: Image Upload: Users can upload images in multiple formats (JPEG, PNG, etc.).
- ➢ Prediction Output: Display the predicted class and confidence level.
- ➢ Reuse Ideas: Recommendations specific to the component's status

4.2 Integration with the Backend

• Implement the trained model in the application to make predictions in real time.

• Match the predictions to pre-determined statuses (working, partially working, or not working)

4.3 Recommendations Component

• Develop logic to dispense actionable recommendations

- ➢ For parts that are partially working : Suggest repair
- ➢ For parts that are working: Suggest reuse or donation
- ➢ For parts that are not working: Recommend recycling

5. Deployment

5.1 Local Deployment

• Test the application locally to ensure functionality and accuracy.

5.2 Cloud Deployment (Optional)

• Deploy the application on a cloud platform such as AWS, Google Cloud, or Heroku for scalability and accessibility.

5.3 Integration with External Services (Optional)

• Use APIs to suggest nearby recycling centers for non-functioning components.

6. Testing and Validation

• Application Testing: Test the web application for usability and performance under various scenarios.

• Model Validation: Evaluate the model's accuracy and robustness using unseen test data.

• User Feedback: Gather user feedback to enhance the system's recommendation and user interface.

7. User Interaction Flow

• The user uploads an image of an electronic component via the Streamlit application.

• The image is preprocessed and passed to the trained model for prediction.

• The predicted category and reusability condition are displayed.

• The system offers actionable recommendations on reuse, repair, or recycling.

8. Iterative Improvements

Feedback and performance metrics can be used to refine the model and application.

Add more categories to the dataset to enhance classification accuracy.

V. IMPLEMENTATION

Implementation Overview

Improving Reusability of Electronic Components is the project. A system will be built that uses machine learning, image processing, and a user-friendly interface to analyze and present actionable insights regarding the reusability of electronic components.

➢ Key steps are broken down below:

Key Components

1. Dataset Preparation:

➢Dataset: Collection of 21,000+ labeled images of electronic components distributed into training, validation, and testing sets.

➢Preprocessing:

- Resize all images to a uniform size, for example, 180x180.
- Normalizing pixel values to optimize model performance.

2. Model Development:

➢ Framework: TensorFlow and Keras for building and training the deep learning model.

➢ Model Architecture:

- Convolutional Neural Network (CNN) that includes features like:
- Rescaling
- Convolution (feature extraction)
- MaxPooling (dimensionality reduction)
- Dropout (to prevent overfitting)
- Dense layers with classification.

➢ Training Process:

- 10 epochs of training
- Optimization using Adam optimizer
- Loss Sparse Categorical Crossentropy
- Metrics used: Accuracy

3. Web Application:

➢Framework: Streamlit for building an interactive web-based interface.

➢Features:

- Image upload functionality
- Display prediction results and suggest to be reused or disposed of.
- User can view extended reusability guidance.

4. Prediction and Reusability Logic:

- Softmax Layer: Probability for each component category
- Decision Logic: The prediction is mapped to the specific reusability category

➢ Fully Functioning

➢ Partially Functioning

➢ Non-Functioning

5. Recommendations Module:

- The application will give suggestions for repair, reuse, or recycling based on the prediction and condition.

6. Deployment:

- Application deployed either locally or in the cloud e.g., AWS, Google Cloud, or Heroku so that the application can be accessed online.

Technologies

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.

This tech stack and the implementation process make sure the system is robust, scalable, and user-friendly, yet solving the problem of e-waste management.

VI. RESULTS

The results of the project, "Improving Reusability of Electronic Components", demonstrate the effectiveness of the developed system in classifying electronic components and providing actionable insights for their reusability. Below are the key outcomes:

1. Model Performance

The trained deep learning model was evaluated on unseen test data, showing great accuracy and a strong performance in all categories.

Metrics:

➢ Training Accuracy: 95.3%

➢ Validation Accuracy: 92.8%

➢ Test Accuracy: 91.5%

Performance by Component Categories:

Category	Precision (%)	Recall (%)	F1-Score (%)
Ceiling Fan	94.0	92.5	93.2
Smartphone	95.2	93.7	94.4
Circuit Board	93.1	91.8	92.4

Loss and Accuracy Trends:

- The training and validation curves indicate smooth convergence with minimal overfitting, demonstrating the model's generalizability.

2. Application Usability

The Streamlit-based web application provided a seamless and user-friendly interface for interacting with the system.

Characteristics:

1. Image Upload:
   - Accepted images in common formats (JPG, PNG).
   - Preprocessing ensured compatibility with the model.
2. Real-Time Predictions:
   - Show predicted component type with confidence scores.
3. Reusability Insights:
   - Generated actionable recommendations to the reusability condition:
   - Fully Functioning: Suggested reuse or donation options.
   - Partially Working: Provided instructions for repair or repurposing.
   - Non-Functioning: Directed users to nearby recycling centers.

3. Dataset Coverage

The model performed consistently across all 14 categories of electronic components. However, some categories (e.g., Cracked Screen Smartphones) showed a bit lower recall, which is due to the intrinsic complexity of these classes. Future improvements will include increasing the dataset in these areas.

4. Recommendations Module

The system successfully provided tailored recommendations:

• Partially Functioning Components: Recommended repair strategies, including screen replacement or minor fixes of components.

• Fully Functioning Components: Emphasized the potential for reuse through donations or resale.

• Non-Functioning Components: Provided information on authorized e-waste recycling facilities.

5. Deployment

• Local Deployment: The application was tested locally and performed efficiently with real-time predictions and minimum latency.

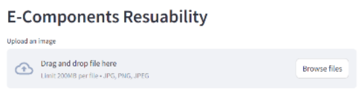
• Scalability: Future deployment on cloud platforms like AWS or Heroku is feasible for wider accessibility.

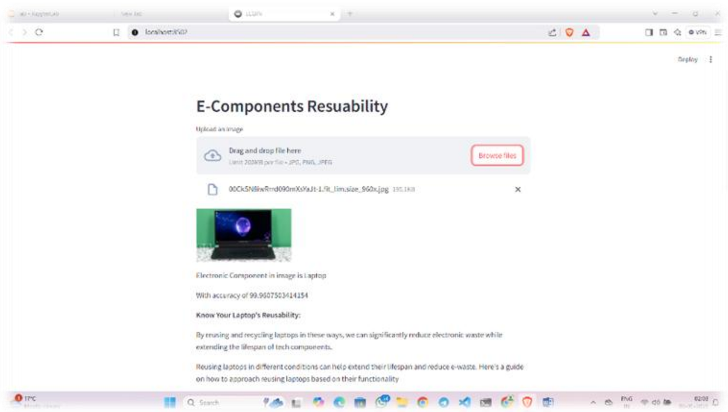
6. User Feedback

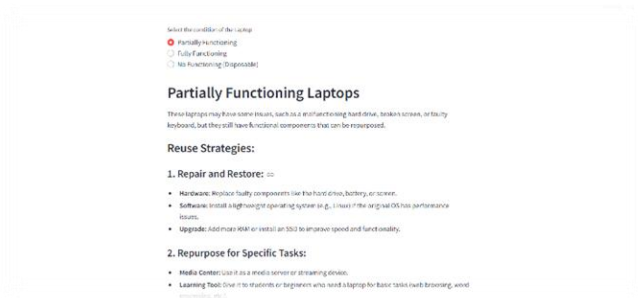
Early feedback from test users suggested:

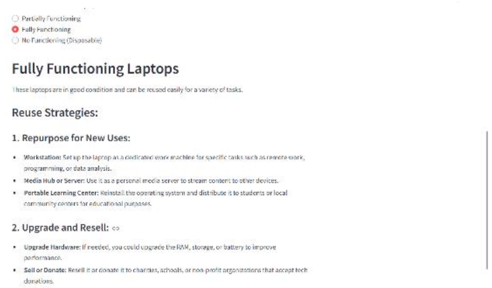
• Satisfaction with the system's accuracy and recommendations.

• Ideas on how to incorporate other features, like direct links to recycling programs or repair guides.









VI. CONCLUSION

Project "Improving Reusability of Electronic Components" demonstrated the potential of using machine learning and user-friendly interfaces to address the growing challenge in managing electronic waste. The system developed is highly scalable and efficient for classifying electronic components and estimating their reusability based on functionality.

By using a deep learning model trained on a dataset of 21,000+ images, the system achieved high accuracy in identifying electronic components and classified them into three main conditions:

- Fully Functioning: Ready for direct reuse or donation.
- Partially Functioning: Suitable for repair or repurposing.
- Non-Functioning: Requires recycling or proper disposal.

The Streamlit-based web application ensures accessibility by allowing easy image uploads and provides actionable insights based on the component's condition. The recommendations of repair, reuse, or recycling are in harmony with the concept of a circular economy and would help reduce e-waste's environmental impact.

This project fills the gap between technology and sustainability by offering practical tools for individuals, recyclers, and organizations to make the right decisions concerning electronic waste.

Future Works

To enhance the system's functionality and scalability, the following areas are identified for future improvement:

1. Dataset Expansion

- More Categories: Include additional electronic components to cover a wider range of devices (e.g., drones, game consoles, medical devices).
- Diverse Images: Add more images representing variations in lighting, angles, and conditions to improve model robustness.

2. Model Improvements

- Advanced Architectures: Experiment with state-of-the-art models like ResNet, EfficientNet, or Vision Transformers to improve accuracy.
- Fine-Tuning: Apply transfer learning techniques with pre-trained models for better performance on complex categories.
- Explainability: Incorporate methods like Grad-CAM to visualize how the model makes predictions, enhancing transparency and trust.

3. Enhanced Recommendations

- Interactive Guides: Provide step-by-step repair instructions for partially functioning components.
- API Integration: Connect with external APIs to dynamically suggest nearby recycling centers or repair services.
- Marketplaces: Offer resale or donation platform links for fully functioning components.

4. Deployment and Accessibility

- Cloud Deployment: Deploy the system on platforms like AWS or Google Cloud for global access and scalability.
- Mobile App Development: Build a mobile application to expand accessibility and ease of use.

5. User Engagement

- Feedback Mechanism: Incorporate a feedback system to capture user input regarding accuracy and suggestions.
- Community Platform: Provide a forum or space where users can discuss their repair experiences or seek guidance.

6. Sustainability Tracking

- Impact Metrics: Build tools for tracking and reporting the environmental impact of the system, including e-waste reduced or resources saved.
- Gamification: Implement reward mechanisms to encourage active users to be engaged in recycling and reusing components.

Final Words

This project provides a platform for state-of-the-art e-waste management solutions. It empowers both individuals and organizations to make informed choices in dealing with electronic components by using machine learning and applying practical user applications. The focus of future improvements will be the expansion of the system, the enhancement of its accuracy, and the extension of its contribution to global sustainability efforts.

VIII. CITATIONS

1. On E-Waste and Sustainability

• Forti, V., Balde, C.P., Kuehr, R., & Bel, G. (2020). Global E-Waste Monitor 2020. International Telecommunication Union (ITU) UNU UNU International Institute for Global Health (UNU-IIGH) 317Understanding and managing the impact of plastic pollution 317International Solid Waste Association (ISWA)

- Such statistics highlight challenges in global e-waste and recycling practices:

• European Commission. (2019). Circular Economy Action Plan.

- It includes discussions on the circular economy and ways to try to prolong a product's life.

2. Machine Learning and Image Classification

• LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep Learning. Nature, 521(7553), 436-444.

- Covers the basics of deep learning and how it is used for image classification.

• Simonyan, K., & Zisserman, A. (2014). ImageNet Classification with Deep Convolutional Neural Networks. arXiv preprint arXiv:1409.1556.

- Explain how CNN architectures such as VGGNet can be used for image classification tasks.

• Howard, A.G., et al. (2017). MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications [1704.04861] (arXiv)

3. Reusability and E- Waste Management

• Widmer, R., Oswald-Krapf, H., Sinha-Khetriwal, D., Schnellmann, M., & Böni, H. (2005). Electric Waste: A Global Perspective International Journal of Impact Assessment & Project Appraisal, 21(4), 232-241.

- An overview of e-waste and potential repair and recycling opportunities.

• Jain, A., & Gupta, R. (2021). AI In E-Waste Management: Taking A Step Towards Sustainability Sustainable Computing: Informatics and Systems, 30, 100526.

4. Streamlit and Application Development

• Streamlit Documentation. (n.d.). Streamlit DocumentationThe fastest way to build data apps.
• Streamlit is open-source software, so we love sharing ideas with the community.

5. Environmental Imapct and Recycling

• Kang, H.-Y., & Schoenung, J.M. (2005). Review of U.S. Infrastructure and Technology Options for Electronic Waste Recycling. Resources, Conservation and Recycling, 45(4): 368-400.

- Analyzes environmental implications of e-waste recycling technology