# Heatmap Visualization for Deep Learning Analysis of Waste Printed Circuit Boards

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***Abstract*—Waste Printed Circuit Boards (WPCBs) are complex multi-material assemblies that present challenges for automated recycling and Critical Raw Material (CRMs) recovery. Visualization of the part of the WPCBs need more attention and contain high-level density CRMs is challenging in computer vision based system analysis. In this work, we propose a deep learning-based multi-label classification framework integrated with heatmap visualization for interpretable WPCB analysis. We fine-tuned the ResNet50 model as backbone and applied binary cross entropy for each class on custom multi-label V-PCB dataset converted from YOLO format. For visualization of the specific regions across the WPCBs with an image, we applied Gradient-weighted Class Activation Mapping (Grad-CAM) that generate class-specific activation maps corresponding to high density CRMs contained components. Experiments on a custom curated V-PCBs dataset achieve a micro-averaged F1 score of 97.67%. The proposed system provides accurate classification along with interpretable heatmaps, supporting automating vision-based disassembly methods and recovery processes in e-waste recycling.**

***Index Terms*—Electronic waste, waste printed circuit boards, computer vision, heatmaps, deep learning**

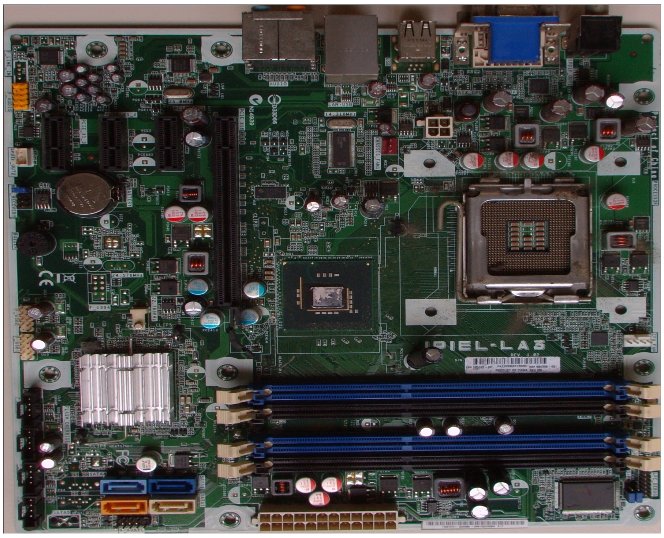
## I. Introduction

Electronic waste, particularly Waste Printed Circuit Boards (WPCBs), contain valuable materials but pose significant recycling challenges. Traditional classification and component identification techniques are manual and labor-intensive [1]. WPCBs are composed of valuable metals, polymers, and ceramics, but their complex multi-layered structures make automated material recovery difficult [1]. Manual disassembly and traditional sorting techniques are inefficient, costly, and pose health risks. Recently, deep learning has shown promise in automating visual analysis tasks [2–4]. However, most black-box models lack interpretability, which is crucial in recycling industries for confident decision-making. In this work, we integrate multi-label classification with heatmap visualization to offer an interpretable AI-based solution for WPCB analysis.

Recent advances in computer vision and deep learning have opened new possibilities for automating WPCB analysis [5]. Deep Convolutional Neural Networks (DCNNs) have demonstrated strong performance in image classification and object detection tasks, specifically in electronic component detection on WPCBs [3]. However, the interpretability of deep models remains a critical concern, especially in industrial applications where understanding model decisions is essential. In parallel, Explainable Artificial Intelligence (XAI) methods such as Gradient-weighted Class Activation Mapping (Grad-CAM) have been developed to visualize the spatial importance of input regions relative to model predictions [6]. Despite significant progress in fields like medical imaging and autonomous driving, the application of explainable deep learning models to e-waste and WPCB recycling remains underexplored. Figure 1 shows the examples of V-PCBs dataset.

In this work, we propose a framework that integrates multi-label classification with Grad-CAM-based heatmap visualization for WPCB analysis. We fine-tune a ResNet50 model [7] using custom V-PCBs dataset converted from YOLO-format labels to multi-label annotations. Our system not only classifies images into multiple component categories but also generates interpretable heatmaps highlighting regions associated with Critical Raw Materials (CRMs). Experimental results demonstrate high classification performance with a micro-averaged F1-score of 97.67%, alongside meaningful visual explanations that can aid selective disassembly and material recovery processes. The main contributions of this paper are the following:

- We developed a multi-label classification framework for WPCBs analysis based on a fine-tuned ResNet50 architecture.
- We convert V-PCBs dataset labels used for electronic



(a)

Fig. 1: Example of high resolution WPCBs from V-PCBs dataset

components detection into multi-label vectors suitable for training deep classification models.
- We apply Grad-CAM to produce class-specific heatmaps that visualize important regions for each each electronic component contains high density of CRMs.
- We evaluate the framework on a our custom V-PCBs dataset [8], achieving a micro-averaged F1-score of 97.67%, and demonstrate the interpretability of the generated heatmaps for recycling and disassembly applications.

The rest of the paper is structured as: Section II present the related work, Section III detailed the methodology along with model training and implementation of Grad-CAM. Section IV represents the experimental results and discussion. Section V conclude the paper.

## II. Related Work

In the literature, different studies have explored object detection for WPCBs disassembly [5, 9], and critical material recovery using computer vision [10]. Explainable AI methods like Grad-CAM [6] have improved model transparency in medical imaging and industrial inspection, but limited efforts target e-waste applications. The disassembly and material recovery of WPCBs have received increasing attention due to the growing volume of electronic waste. Traditional recycling processes often involve shredding and chemical treatments, leading to material loss and environmental concerns. To address these challenges, recent studies have applied computer vision and deep learning techniques for selective disassembly. This paper [9] proposed a deep learning-based approach to selectively disassemble WPCBs by detecting and locating selected electronic components such as capacitors and integrated circuits. Their method demonstrated the feasibility of using object detection models like YOLOv3 to automate component recognition. Similarly in [11], authors used Real-Time Detection Transformer (RT-DETR) model to detect and localize different electronic components from WPCBs. They compared the results with other state of the art object detection models on V-PCBs dataset and compare the results in real-time. In another study [10], authors applied machine vision techniques for identifying critical material zones, facilitating improved recovery rates [12, 13]. However, despite the success of detection models in recognizing components, these models often function as black boxes, providing no insight into the spatial reasoning behind predictions. In industrial recycling environments, interpretable decision-making is crucial to ensure process reliability and operator trust. Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM [6] have been widely adopted in fields like medical imaging to visualize the spatial importance of input features in CNN decisions. Grad-CAM enables the generation of class-specific heatmaps that localize regions contributing to a given prediction, improving model transparency. Inspired by these advances, our work integrates multi-label deep learning classification with Grad-CAM-based heatmap visualization specifically tailored for WPCB images. By linking classification outputs to visual regions of importance, our approach enhances the interpretability of electronic component analysis and supports more informed disassembly, sorting, and material recovery strategies.

## III. Methodology

This section explains the detailed methodology followed to perform the heatmap visualization analysis of WCPBs using deep learning model. The figure 3 shows the detailed block diagram of the proposed methodology.

### A. Dataset Preparation

We used a custom dataset called V-PCBs dataset developed locally in our lab under industrial environment such as varying lighting conditions, different camera viewpoints. The dataset consist of 747 high resolution images of WPCBs. We converted 70%, 15%, and 15% into training, validation, and test sets, respectively. The dataset is annotated according to the YOLO object recognition format. Each image contains bounding box annotations for multiple electronic components. We selected eight classes, such as capacitor, electrolytic capacitor, transistor, diode, resistor, integrated circuit (IC), transformer, and coil, based on the presence of CRMs. In the next step, we converted the YOLO format labels into multi-hot label vectors for multi-classification.

### B. Model Architecture

We adopted famous ResNet50 [7] model pre-trained on ImageNet dataset. The last fully connected layer is replaced with a new linear layer outputting eight different nodes, corresponding to the eight electronic component classes. A sigmoid activation is applied to each output node to model independent class probabilities. The model is optimized using the Binary Cross-Entropy with Logits Loss (BCEWithLogitsLoss) and trained using the Adam optimizer with a learning rate of

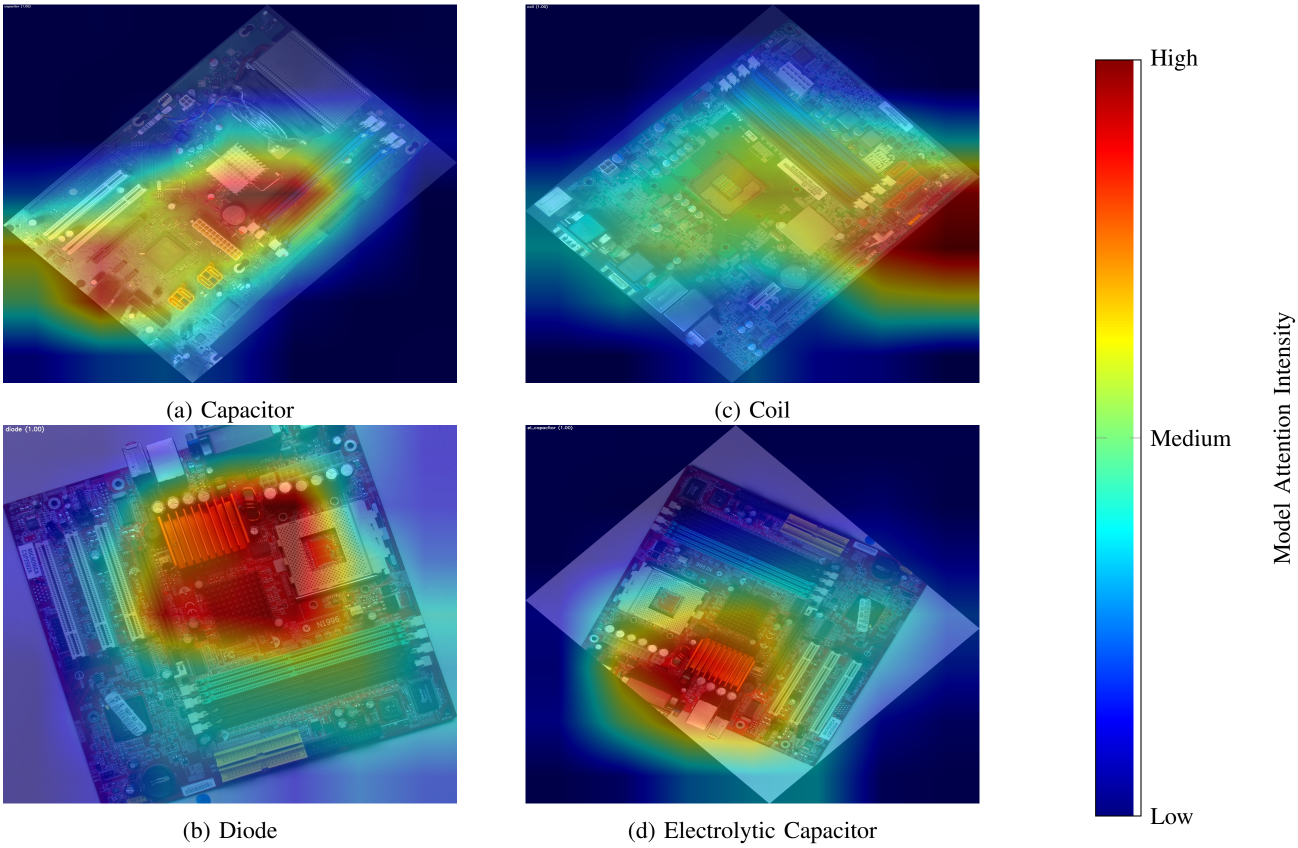



Fig. 2: Heatmaps for various PCB components with shared model attention scale. Red regions indicate high class-specific attention.

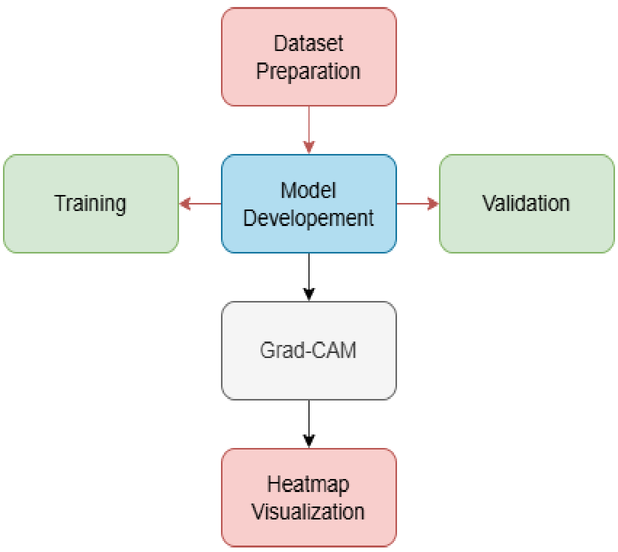



Fig. 3: Block diagram of detailed methodology adopted for heatmap visualization of WPCBs using deep learning

$5 \times 10^{-4}$ and a batch size of 16. The model is trained for 20 epochs, with early stopping based on validation loss. Evaluation metrics include micro-averaged F1-score, training and validation loss curves, and multi-label confusion matrices for each class. Heatmaps are generated for the top-2 predicted classes above a probability threshold of 0.5. The resulting visualizations are overlaid on the original images and saved for analysis.

### *C. Heatmap Visualization Using Grad-CAM*

To make the model decisions interpretable, we employ Grad-CAM [6]. Grad-CAM produces visual explanations by highlighting WPCBs regions that contribute most to the model's prediction for a given class. The high density of red represent that during the training, the model put attention on that specific region of the board for a specific class. For instance in Fig. 2a the red area represents the high learning intensity in that region for class of capacitor.

The process of generating a class activation heatmap using Grad-CAM involves several sequential steps. First, a forward pass is performed through the network, extracting the output feature maps from a specified convolutional layer (e.g., layer4 in ResNet50). Next, the gradients of the target class score with respect to these feature maps are computed via backpropagation, highlighting regions critical for the model's prediction.

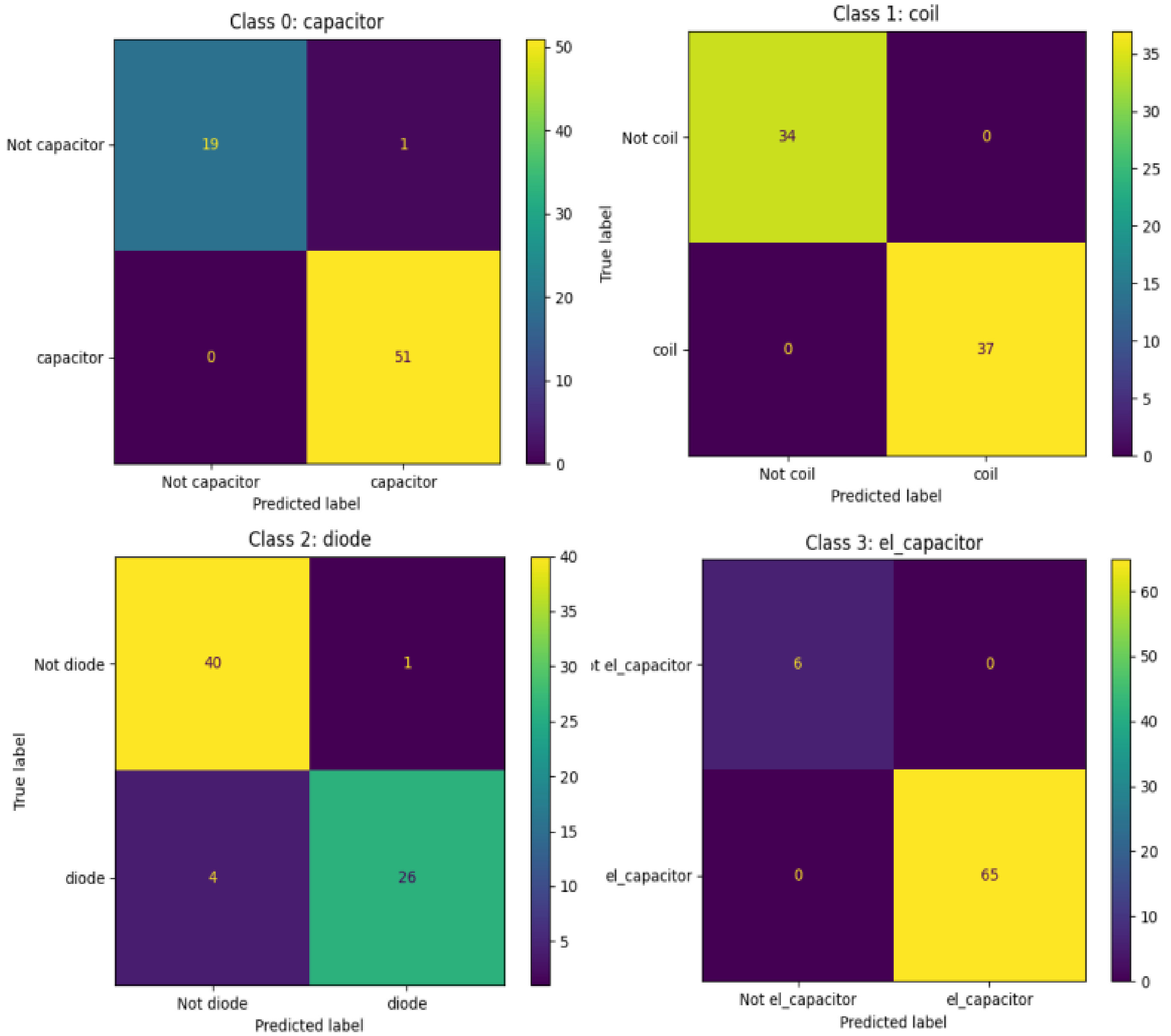



Fig. 4: Confusion matrix of four different classes present on WPCBs.

These gradients are then globally averaged to produce a set of weights, which are used to linearly combine the corresponding feature maps. The resulting weighted combination forms a coarse heatmap that emphasizes influential spatial regions. To refine the visualization, a ReLU activation is applied to retain only positive contributing features, followed by normalization to enhance contrast and resizing to match the original image dimensions. This final heatmap localizes the image regions that most strongly influenced the model's class-specific decision. These heatmaps provide spatially localized visualizations indicating critical regions related to each component category, enabling a better understanding of model behavior during its training.

## IV. Results and Discussion

We conducted the experiment on our local server, which is equipped with an NVIDIA GPU and uses PyTorch as the deep learning framework with Python 3.11.

To further understand model performance, multi-label confusion matrices were generated for each class. Figure 4 illustrates an example confusion matrix for four different classes. High true positive rates were observed across all major classes, indicating effective learning of diverse component features. It shows the number of positive detection of each class with in board. For instance in Fig. 4 capacitor shows that the classification results of the model over complete set of dataset, 51 considered as true positive and 19 represent the true negative. The combination of high predictive accuracy and interpretable heatmaps suggests that the proposed framework is effective not only for automated WPCBs classification but also for supporting selective disassembly and targeted CRMs recovery processes.

We use Grad-CAM that allowed us to see which parts of the WPCBs the model focused on when making predictions. The heatmaps presented in the results section highlighted the important electronic components likely to contain high density CRMs, showing that the model is learning the correct patterns. This makes the system accurate and trustworthy. It could be useful in real recycling processes driven by automated computer vision systems.

## V. Conclusion

This paper presented a deep learning-based framework for interpretable analysis of Waste Printed Circuit Boards (WPCBs) using multi-label classification and heatmap visualization. By fine-tuning a ResNet50 model on a multi-label converted WPCB dataset and employing Grad-CAM for heatmap generation, we achieved both high classification performance (micro-averaged F1-score of 97.67%) and enhanced model interpretability. The integration of Grad-CAM heatmaps allows spatial localization, providing valuable insights to support selective disassembly and material recovery efforts in e-waste recycling processes. Our experiments demonstrate that deep learning models, when combined with explainability techniques, can significantly contribute to automation, transparency, and efficiency in industrial recycling applications.

Future work will involve a detailed analysis of WPCBs to identify the Critical Raw Materials (CRMs) present in different types of boards. From a recycling perspective, this will help to estimate the value of the CRMs.

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