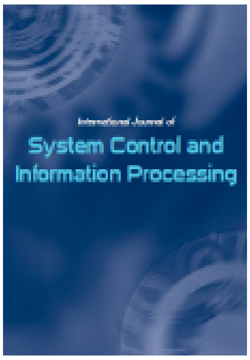

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PCBA defect classification in real world with out-of-distribution detection

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Abstract: Inadequate chip solder joints can significantly impact the overall quality of finalised Printed Circuit Board (PCB) products. Detecting all solder joint defects in real time and adaptively during the actual production process poses a formidable challenge due to the diverse nature of these defects and the limited availability of anomaly data. In contrast to the conventional Printed Circuit Board Assembly (PCBA) defect classification task that is limited to pre-labelled defects, we propose adaptive classification algorithms capable of identifying new categories of defects and ensuring accurate classification of labelled categories. Specifically, we developed a multitasking network that utilises Swin-Transformer as the underlying architecture to classify labelled categories and identify novel defective categories. And neuronal activation coverage is designed to detect unseen types of PCBA defects. Furthermore, we propose an end-to-end unsupervised hashing algorithm that incorporates novel category discovery for images classified as previously unseen categories. Finally, we conducted experiments on a variety of different backbone networks in real PCBA defect datasets to demonstrate the effectiveness of our proposed method.

Keywords: solder joints; defect classification; OOD; out-of-distribution; novel category discovery.

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1 Introduction

The electronic components were usually packaged in dual in-line package (DIP) packages, where the pins are arranged in two rows on either side of the component. However, as the miniaturisation and high-density requirements of electronic devices increase, surface mount technology (SMT) packages are gradually replacing DIP packages. SMT packages reduce the size and weight of components by soldering them directly to the surface of Printed Circuit Board (PCB) (Ulger et al., 2023), improve the assembly efficiency and reliability of circuit boards, and achieve high-density, high-reliability, miniaturisation, and low-cost of electronic product assembly, as well as automated production. In the production process of the SMT line, due to the complexity and variability of the process leads to Printed Circuit Board Assembly (PCBA) defects, jeopardising the function of the product. According to the location and manifestation of defects (Luo et al., 2022) the defects are divided into surface defects and structural defects. Surface defects mainly appear in the local location of the product surface, usually manifested as texture, pattern, colour and other abnormalities, such as surface cracks, colour blocking and wrong text printing, etc.; structural anomalies are mainly caused by the product's structural errors, mainly manifested as cracks in the product, bubbles, deformation and so on. Structural defects are one of the main types of defects in assembled circuit boards, including insufficient solder, voids and short circuits (Leinbach and Oresjo, 2001).

PCBA production line defect detection can be specifically divided into manual visual inspection and automated optical inspection (AOI), in some of the detection of higher precision requirements of the production line, to take the two joint inspection, that is, after the AOI test, the manual rejudgement. Most of the early AOIs used systems based on a set of expert predefined rules such as image recognition (Anitha and Rao, 2023), template matching (Ibrahim et al., 2011; Chauhan and Bhardwaj, 2011) etc. Due to advancements in PCBA production line processes, rule-based systems are gradually being replaced by data-driven model-based systems due to their complexity and cumbersome nature. Numerous supervised and unsupervised deep learning algorithms have been employed to enhance the accuracy of AOI in detecting soldering defects (Zhou et al., 2023). To ensure high yield and save labour costs, Wu et al. (2021) applied two target detection networks for PCB defect detection and classification tasks. Shen et al. (2020) propose LD-PCB for real-time lightweight PCB type detection, and CR-PCB for rapid and robust character recognition. The aforementioned supervised methods heavily rely on a substantial number of PCBA defect samples to acquire a robust generalisation capability. However, the actual production setting lacks sufficient amounts and variations of defect data, making it challenging to label samples due to significant human and material resource requirements. Numerous studies have been conducted on unsupervised-based defect detection, which has exhibited remarkable advancements in performance compared to traditional supervised methods (Zhou et al., 2023). By integrating Siamese network similarity measurements with an encoder-decoder semantic segmentation framework, Ling et al. (2022) effectively detect minute defects while mitigating overfitting issues caused by limited defect samples, through the utilisation of shared encoders, a decoder, and correlation modules to seamlessly incorporate deep features and restore spatial information. You (2022) proposed a PCB defect detection method based on Generative Adversarial Networks, which uses edge-enhanced super-resolution GAN (EESRGAN) to enhance the PCB image and accomplish super-resolution detection of reconstructed images, and used different preprocessing models for end-to-end training of PCB images. All of the above unsupervised methods are addressing the problem of insufficient defect samples faced in the field of PCBA defect detection, and have achieved certain results. However, due to the offline training approach, they are unable to solve the difference between the real-time data flow distribution of the production line and the training data. The model can only identify whether the component is defective or not, but not the type of defect. In the long run, forming an inspection system based on this model does not provide effective positive feedback to the upstream process, which in turn does not improve the production process. In this paper, we define the problem as the PCBA defect classification problem in the real case, i.e., how to make the PCBA defect classification model trained with limited labelled samples adaptive to the new class of defects while recognising the old class.

Inspired by the research of OCD (Du et al., 2023) as well as out-of-distribution (OOD) problem (Liu et al., 2023), in order to solve the PCBA defect detection problem in real scenarios, this paper proposes a multitasking network based on OOD detection and unsupervised Hash Code. Our contributions are summarised as follows:

- A real-world PCBA defect categorisation problem is defined, as well as a PCBA defect dataset is constructed to establish a robust benchmarking review.
- The proposed approach introduces a multi-task PCBA defect network to enhance the self-adaptive capability of the network model, and subsequent ablation experiments are conducted on various backbone networks.

Firstly, self-supervised learning is used to pre-train the backbone network on a large amount of unlabelled data collected, so as to improve the feature extraction capability of the network and reduce the impact of the scarcity of defect samples. Secondly, a two-branch network is designed to achieve the discovery of the new PCB defect class by using the OOD detection algorithm and the deep hash features. Finally, the surface mount defect detection network is updated by using the FOSTER class incremental learning algorithm to update the surface mount defect detection network weights to achieve model adaptivity.

The remaining sections of this paper are structured as follows: Section 2 provides a comprehensive review of the existing literature on Novel category discovery and generalised category discovery (GCD), OOD analysis, and unsupervised deep hash coding. In Section 3, we present our proposed method in detail, which includes a unsupervised hashing coding network and the discovery of generalised defect categories in PCBA. Experimental results and discussions on the effectiveness of our approach are presented in Section 4. Finally, we conclude our findings in Section 5.

2 Related work

2.1 Generalised category discovery (GCD)

The NCD problem assumes that all unlabelled images belong to the new category, which deviates from a realistic scenario and lacks practicality. The present work by GCD (Vaze et al., 2022) introduces the initial problem formulation of generalised new class discovery and proposes a fusion of self-supervised, unsupervised representation learning, and semi-supervised K-means clustering techniques to accomplish new class discovery and estimate the number of unlabelled data categories. DPN (An et al., 2023) is a novel model that effectively addresses the limitations of coupled training approaches by decoupling known and novel categories, explicitly transferring category-specific knowledge, capturing high-level semantics, and learning more discriminative features through semantic-aware prototypical learning (SPL). To tackle the GCD problem, the study conducted by semi-GMM (Zhao et al., 2023) introduces an innovative EM-like framework which effectively integrates representation learning with class number estimation by employing a semi-supervised adaptation of the Gaussian Mixture Model. Further, Zhao and Mac Aodha (2023) combine the GCD problem with incremental learning to propose a new incremental generalised category discovery (IGCD) method that combines nonparametric classification with efficient image sampling to mitigate catastrophic forgetting, and, present a new benchmark dataset called iNatIGCD, which is motivated by real-world fine-grained visual classification tasks.

2.2 Out-of-distribution (OOD)

The objective of OOD detection is to differentiate between InD and OOD data inputs, thereby abstaining from utilising unreliable model predictions during deployment. The existing detection methods can be broadly classified into four categories:

1 classification-based

2 density-based

3 distance-based

4 reconstruction-based approaches (Yang et al., 2021).

Classification based methods aim to improve the OOD performance by utilising neural network outputs, including post-hoc detection (Liu et al., 2020), label space redesign (Huang and Li, 2021), Bayesian models (Nandy et al., 2020), etc. Develop density-based methods for detecting OOD data by creating probabilistic models to represent in-distribution data and identifying test data located within low-density regions as OOD (Jiang et al., 2021). Distance-based methods discern OOD instances by evaluating their proximity to the centroid or prototype of the distribution class (Ming et al., 2022). Some methods (Chen et al., 2020) also leveraged contrastive learning to enlarge the distance between ID and OOD. The fundamental concept of the reconstruction-based approach (Zhou, 2022) lies in utilising an encoder-decoder framework trained on ID data, which inherently yields disparate outcomes for both ID and OOD samples, thereby enabling effective anomaly detection.

Specifically, through certain OOD assays that induce alterations in neuronal behaviour. LINe (Ahn et al., 2023) aims to identify significant neurons by employing the Shapley value and subsequently applies activation clipping techniques. Through analysing neuronal activation patterns(NAP) in ReLU-based architectures, Olber et al. (2023) propose utilising binary neuronal activation patterns for detecting OOD samples.

2.3 Unsupervised deep hash coding

Deep unsupervised image hashing leverages the semantic information acquired by pre-trained deep neural networks to effectively map high-dimensional unlabelled image data into a low-dimensional binary coding space. However, how to infer semantics information and how to utilise semantics information for learning hash codes are two key problems here (Luo et al., 2023). According to the principles of semantic learning, unsupervised methods can be broadly categorised into three main groups: similarity reconstruction-based approaches, pseudo-label-based techniques, and prediction-free self-supervised learning methods. Typically, similarity-based reconstruction methods (Luo et al., 2021) generate pairwise semantic information and subsequently employ techniques for preserving pairwise semantics to facilitate hash code learning. Semantic structure-based unsupervised deep hashing (SSDH) (Yang et al., 2018) study pioneers the application of the fast VGG network (VGG-F) model for deep feature extraction and hash code learning in this field. The pseudo-label-based approaches leverage pseudo-labels as a form of semantic information to facilitate the learning process of hashing. the majority of researchers employed clustering techniques (Dong et al., 2020) and Bayes' rule (Zhang et al., 2017), among other methods, to generate pseudo-labels. The self-supervised learning approaches for hashing coding are conducted a self-supervised paradigm. While earlier approaches typically imposed certain constraints on hash coding by minimising the regularisation term, more recent advancements in contrastive learning have demonstrated promising performance in generating discriminative representations across various domains.

Here is a brief overview of some self-supervised hashing coding. After applying data augmentation to obtain diverse perspectives of an image, self-supervised product quantisation (SPQ) (Jang and Cho, 2021) generate quantised features that aim to maximise the cross-similarity between consecutive representations from one angle and the quantised features derived from another angle. In response to the existing methods that mainly focus on instance comparison learning without considering the underlying semantic structure information, SSCQ (Wu et al., 2022) includes partially consistent quantisation and globally consistent quantisation self-supervised consistent quantisation methods.

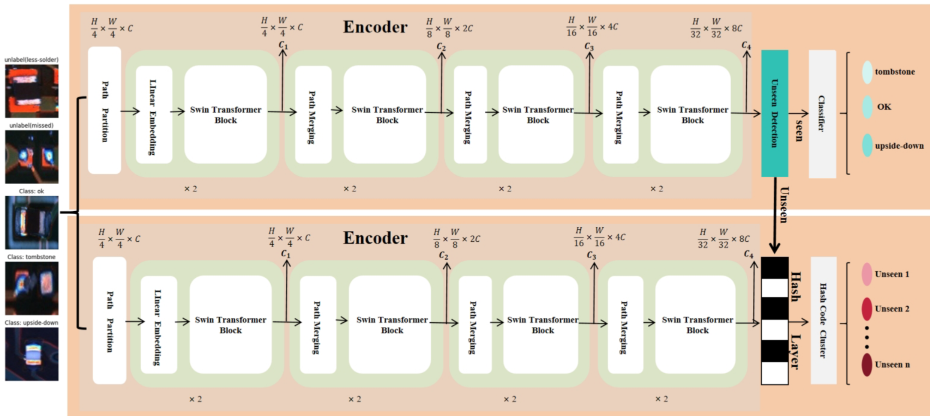
3 Methodology

3.1 Overview

In this paper, we focus on facilitating machine learning in recognising unknown PCBA defect classes and present the problem of on-the-fly PCBA defect class discovery (OCD), wherein the algorithm demonstrates its capability to identify defect classes that are absent from the training set in real-world scenarios. The problem of instant PCBA defect OCD is defined as follows: The complete dataset D consists of two parts, namely the labelled dataset $D_l = \{(\mathbf{x}_i, y_i)\}_{i=1}^{\mathcal{N}} \in X \times Y_l$ and the unlabelled dataset $D_u = \{(\mathbf{x}_i, y_i)\}_{i=1}^{\mathcal{M}} \in X \times Y_U$, where $Y_l \in Y_U$, x_i denotes samples within the dataset and y_i is the corresponding labels. The defect type discovery model is denoted $p = C_w(f_\theta(X))$, which consists of a feature extraction module $f_\theta(*)$ and a new class discovery module $C_w(*)$. where θ and w denote the corresponding parameters of the model, and x denotes the input PCBA defective image data. The defect class discovery model p is trained on the labelled dataset D_l to effectively classify the PCBA defect present in the unlabelled dataset D_u. The differences between OCD and GCD lie in: samples in the unlabelled dataset D_u are individually inferred, i.e., instant feedback (Du et al., 2023).

In this section, we present the methods proposed to address OCD in PCBA defects. Initially, drawing inspiration from ResidualTuning (Liu and Tuytelaars, 2022), we propose a two-branch multitasking defect classification and novel category of defect discovery network, see in Figure 1. Following the supervised learning paradigm, one branch of this network is dedicated to classifying and addressing the OOD problem, while the other branch utilises unsupervised hashing methods to generate hash codes for unknown input images categories. Once the input image is judged to be of unknown classification, it is classified based on the hash code of another branch. This approach not only ensures accurate classification of known categories but also resolves the clustering issue associated with unknown categories.

Figure 1 New defects class discovery of the proposed framework (see online version for colours)



3.2 *Detecting unseen PCBA defects via neuron activation coverage*

To investigate novel categories of defects in PCBA, we utilise neuron activation coverage (NAC) (Liu et al., 2023) for uncertainty estimation, wherein the NAC scores of all neurons are directly averaged to determine the uncertainty of input samples.

In PCBA defect classification models, the focus is typically limited to the forward propagation of a neuron from the previous layer to the next layer, neglecting its impact on subsequent neurons. To address this limitation and determine whether an input image belongs to a known class of defects, it becomes essential to effectively quantify the neuron activation state of a known defective image. Motivated by the work of Huang et al. (2021), we incorporate gradients backpropagated from the KL divergence between the network output and a uniform vector to effectively model neuron influence.

$$D_{\mathrm{KL}}(\mathbf{u}||\mathbf{p}) = \sum_{i=1}^{C} u_i \log \frac{u_i}{p_i} = -\sum_{i=1}^{C} u_i \log p_i - H(\mathbf{u}) \tag{1}$$

where $u = [1/C, 1/C, ..., 1/C]$, $p = softmax(g(z))$, $z = f_\theta(X)$, p_i denotes i-element in p, $H(u) = -\sum_{i=1}^{C}$ is a constant. Now, we can formulate neuron activation state as,

$$\hat{\mathbf{z}} \quad = \sigma(\mathbf{z} \odot \frac{\partial D_{\mathrm{KL}}(\mathbf{u}||\mathbf{p})}{\partial \mathbf{z}}) \tag{2}$$

$$= \sigma\big(\mathbf{z} \odot (\left(\frac{\partial g(\mathbf{z})}{\partial \mathbf{z}} \cdot \frac{\partial D_{\mathrm{KL}}}{\partial g(\mathbf{z})}\right)) \tag{3}$$

$$= \sigma\big(\mathbf{z} \odot (\frac{\partial f(X)}{\partial \theta} \cdot (p - u))\big) \tag{4}$$

where $\frac{\partial D_{KL}}{\partial g(\mathbf{z})} = (p - u)$ measures how model predictions deviate from a uniform distribution, thus denoting sample confidence (Huang et al., 2021), $\sigma(x) = \frac{1}{1+e^{-\alpha x}}$ is the sigmoid function with a steepness controller α, $\hat{\mathbf{z}}$ to represent the neuron state function.

By explicitly defining the state of neuronal activation, we can effectively induce the functionality of neuronal activation coverage (NAC) to accurately characterise the behaviour of neurons in both known and unknown scenarios involving PCBA defects. The objective of NAC is to quantitatively assess the extent of coverage of neuronal states by known PCBA defects using a probability density function. Consider a given datasets X of PCBA defects as input to a neural network, where the state of its **i**th neuron is denoted by $\hat{\mathbf{z}}_i$ and its probability density function(PDF) is represented by $\kappa^{i}_{X}(\cdot)$. Then, NAC can be defined as follows.

$$\Phi^i_X(\hat{z}_i; r) = \frac{1}{r}\min(\kappa^i_X(\hat{z}_i), r) \tag{5}$$

where $\kappa^{i}_{X}(\cdot)$ is the probability density of $\hat{\mathbf{z}}_i$ on the set X, r denotes the lower bound for full coverage of the state $\hat{\mathbf{z}}_i$.

After formulating the NAC functions for defects data of known, we can easily employ this function to detect unseen types of PCBA defects.

$$D(\mathbf{x}^*) = \begin{cases} \text{seen} & \text{if } S(\mathbf{x}^*; \hat{f}, X) \geq \lambda; \\ \text{unseen} & \text{if } S(\mathbf{x}^*; \hat{f}, X) < \lambda, \end{cases} \tag{6}$$

$$S(\mathbf{x}^*; \hat{f}, X) = \frac{1}{N}\sum_{i=1}^{N} \Phi^i_X(\hat{f}(\mathbf{x}^*)_i; r), \tag{7}$$

where N is the number of neurons, $S(*)$ is the uncertainty score, $\hat{f}(\mathbf{x}^*)_i$ the activation state of ith neuron, λ is a threshold, r is the controller of NAC function. Obviously, the inputs $\mathbf{x}^*$ with uncertainty scores $S(*)$ less than λ will be classified as unseen defect types; conversely, they will be categorised as seen defect types.

3.3 Unsupervised hashing for PCBA defects

In order to achieve instant feedback, the clustering technique widely used in GCD is no longer practical. To establish decision boundaries for PCBA defect categories (both known and unknown), the most straightforward approach is to determine thresholds based on the minimum distance between categories. However, relying solely on metric-based decision making is inadequate for reasoning about individual samples, novel categories lacking prototypes, and fails to fully exploit existing defect category labels. To facilitate the online identification of known defective categories of PCBAs and enable the recognition of unknown categories, we adopt the concept of Deep Hash to map an input image x to a K-dimensional binary code $b \in \{-1, +1\}^K$ in Hamming space with inherent decision boundaries. Ideally, each category corresponds to a specific hash code. To achieve the aforementioned objective, we employ an optimised $f(X; \theta)$ to acquire the real-valued features of image X. Subsequently, Sign(*) is utilised to derive the hash code b, as indicated below.

$$b_i = sign(g(f(x_i; \theta))) \in \{-1, 1\}^L \tag{8}$$

where the input image is denoted as x_i, the input sequence number is denoted as i; L represents the length of hash code. The feature extraction backbone network is represented by $f(X;\theta)$, and the projection head is represented by g(*).

For a given image x, we partition it into n fixed-size image segments through random cropping and overlapping. Subsequently, the same standard enhancement technique as VICReg is applied to these cropped image segments, resulting in individual segments denoted as x_1, ..., x_n. We denote x_i as the ith augmented image patch from x. For each image patch x_i, we obtain its hash code $b_i = sign(\mathrm{z}_i)$ by equation (8).

Total training loss. Inspired by (Jang et al., 2022), the cosine similarity between hash codes z_i and z_j can be utilised to approximate the Hamming distance between the binary codes b_i and b_j as:

$$D_{\mathrm{H}}(\mathrm{b}_i, \mathrm{b}_j) \simeq \frac{K}{2}(1 - Cos\left(\mathrm{z}_i, \mathrm{z}_j\right)) \tag{9}$$

Then, the proposed unsupervised hashing loss is computed as:

$$\mathcal{L}_{uh}(\mathrm{z}, \bar{\mathrm{z}}) = 1 - Cos(\mathrm{z}_i, \bar{\mathrm{z}}) \tag{10}$$

where $\bar{\mathrm{z}} = \sum_{i=1}^{n} \mathrm{z_i}$. Overall, the training objective is:

$$\mathcal{L}_{total} = L_{uh} + \mathcal{L}_{bce} \tag{11}$$

The explanation of $\mathcal{L}_{bce}$ will be provided in the subsequent section.

3.3.1 Gaussian distribution estimator

Ideal category hash codes should represent the category-level semantics; however, features may respond to instance-level semantic expressions in practice (Du et al., 2023), and, data augmentation during unsupervised training destroys the features obtained by the same images, which in turn destroys the consistent representation. To address this, we employ a pre-defined Gaussian distribution estimator (equation (12)) with mean m and standard deviation σ to assess the binary likelihood of hash code element h. Considering the deep hashing as a binary classifier for the sign of each bit, we make the assumption that PCBA defective images belonging to the same category exhibit a consistent hash value, which can be effectively estimated through maximum likelihood problem.

$$g(h) = \exp\left(-\frac{(h-m)^2}{2\sigma^2}\right) \tag{12}$$

The likelihood and binary cross entropy-based (BCE) loss are computed by employing two estimators: g^+ with $m = 1$ and g^- with $m = -1$, both having the same σ, as:

$$\mathcal{L}_{bce}(\mathrm{x}_i) = \frac{1}{L}\sum_{k=1}^{L}\left(H_b\left(b_k^+, g_k^+\right) + H_b\left(b_k^-, g_k^-\right)\right) \tag{13}$$

where $H_b(x, y) = -\left(x \log y + (1-x)\log(1-y)\right)$ is a BCE. $g_k^+ = g^+(b_k)$, $g_k^- = g^-(b_k)$ represents the ith estimation of the likelihood of a hash code, and b_k^+, b_k^- denotes binary likelihood labels which are obtained as:

$$b_k^+ = \frac{1}{2}\left(\mathrm{sign}(b_k) + 1\right), b_k^- = 1 - b_k^+ \tag{14}$$

3.3.2 Error decay estimator

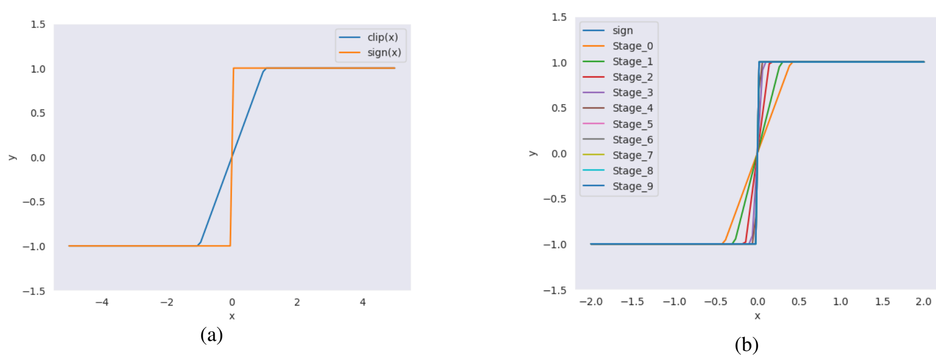
The non-differentiability issue of the Sign function must be addressed in order to achieve end-to-end unsupervised hashing framework. The available options surpass straight through estimation (STE) and approximate fitting in terms of their superiority. While the former method avoids computing the gradient function, it significantly compromises the flexibility of the deep hashing model. Therefore, we introduce the Error Decay Estimator (EDE) method, which employs Sign(*) for direct quantisation during forward propagation and utilises equation (15) to fit the gradient during backpropagation. From Figure 2, it can be seen that the method we introduced can effectively reduce the fitting error.

$$g(x) = ktanh(tx) \tag{15}$$

$$\mathrm{t} = \mathrm{T_{min}} 10^{\frac{\mathrm{i}}{\mathrm{N}} \mathrm{x} \log \frac{\mathrm{T_{max}}}{\mathrm{T_{min}}}}, \mathrm{k} = \max(\frac{1}{\mathrm{t}}, 1) \tag{16}$$

where g(*) represents the approximation function of the backpropagation process, k and t serve as temperature that varies with the number of training sessions, T_{max} and T_{min} are hyperparameters.

Figure 2 Comparison of different fitting functions: (a) compare clip(x) with sign(x) and (b) compare ktanh(tx) with sign(x) (see online version for colours)



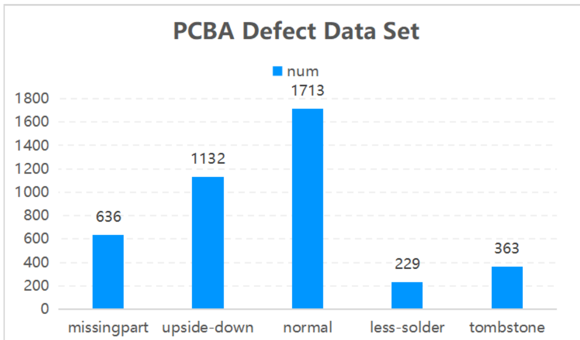
4 Experiments

4.1 PCBA datasets and metrics

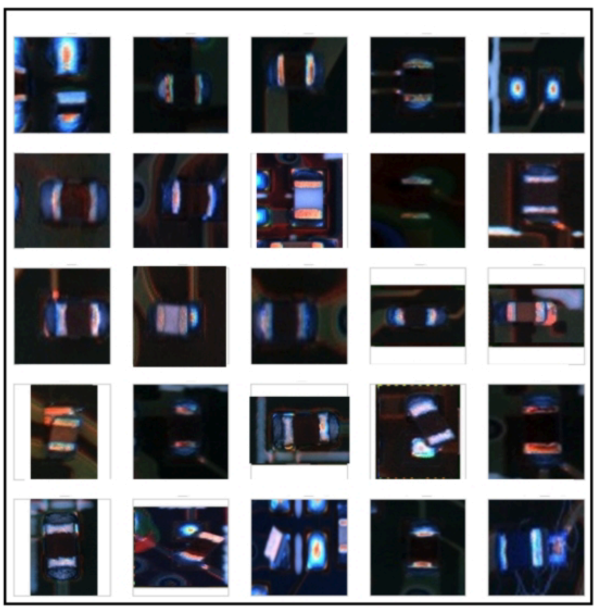
PCBA datasets. In order to validate our proposed method, we have developed a PCBA dataset, as illustrated in Figure 3. The dataset comprises a total of 4070 images, encompassing five types of defects: insufficient solder, missing components, normal condition, tombstone effect, and upside-down placement.

During the initial acquisition of PCBA defect images, due to the disproportionate number of normal samples compared to defect samples in actual production, it is necessary to ensure a uniform distribution of samples in the dataset for neural network training. Therefore, some data are excluded during the filtering process to achieve a more balanced distribution of training samples. The final dataset consists of 1710 normal samples, 1132 upside-down defects, 636 missingpart defects, 363 tombstone defects, and 229 less-solder defects. Prior to model training, we selected three types of defects as labelled data, while the remaining types of defects were treated as unlabelled data. The entire dataset was then randomly divided into a training dataset and a test dataset in an 8 : 2 ratio.

Figure 3 Introduction to PCBA defect datasets: (a) number of PCBA datasets and (b) schematic of PCBA datasets (see online version for colours)



(a)



(b)

Evaluation metrics. For unknown PCBA defect detection, We utilise two threshold-free metrics in our evaluation:

1 FPR95: the false-positive-rate of unseen PCBA defect samples when the true positive rate of seen samples is at 95%

2 AUROC: the area under the receiver operating characteristic curve. For new category of PCBA defect discovery, we adopts the StrictHungarian for comprehensive comparisons. The protocol are used by Fini et al. (2021) and Vaze et al. (2022), respectively, and their difference is clearly illustrated in (Vaze et al., 2022).

For the StrictHungarian, the accuracy of the whole query set is first calculated, which prevents the situation that a cluster is repeatedly used by the 'New' and 'Old' categories. The accuracy calculation via Hungarian algorithm can be formulated as

$$Acc = \max_{s(\cdot)\in\mathcal{S}(Y_U)} \frac{1}{|D_U|} \sum_{i=1}^{|D_U|} 1[\hat{y}_i = s(y_i)] \tag{17}$$

where D_U is previously unencountered categories of PCBA defects, y_i is the ground truth label, $\hat{y}_i$ is the predicted label decided by cluster indices, and $\mathcal{S}(\mathcal{Y}_\mathcal{U})$ is the set of all permutations of ground truth labels.

4.2 Implementation details

All experiments are classified based on the backbone models employed, including ResNet50 (a traditional CNN), ConvNext (another recently traditional CNN) (Liu et al., 2022), Swin-Transformers(vision transformers) (Liu et al., 2021), and CMT (a combination of CNN and Transformers) (Guo et al., 2022). To ensure consistency in training conditions, we utilised the PyTorch framework along with the image enhancement capabilities provided by kornia library (Riba et al., 2020). For detecting unseen categories of PCBA defect, we compare approach with several recently proposed methods (Hendrycks and Gimpel, 2016; Liang et al., 2017; Liu et al., 2020; Huang et al., 2021) on our dataset. For the new class of unsupervised hashing discovery of PCBA defects, we evaluate the impact of our proposed methodology on various backbone architectures. We employ Adam optimiser and decay the learning rate with cosine scheduling for training multitasking network, and, the experiments are performed on the ubuntu system with a NVIDIA RTX 3090.

Detecting unseen category of PCBA defect. In all experiments, we first modelled the NAC function (see equation (5)) using the known label of PCBA dataset and then applied the equation (7) to calculate the uncertainty

Results. As demonstrated by the results presented in Table 1, our employed method exhibits exceptional efficacy in detecting previously unseen defects in PCBA, thereby establishing a benchmark for such detection. We compare the impact of backbone network models with different infrastructures on the detection of unseen PCBA defects and observe that Swin-T, utilising transformer as its underlying architecture, achieves State-of-the-Art (SoAT) performance in identifying previously unencountered categories of PCBA defects.

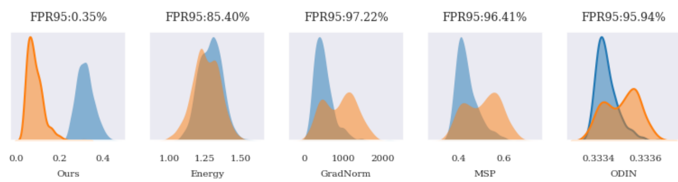
Unsupervised hashing for new category of PCBA defect discovery. To determine if the image belongs to a previously unseen category, we employ the PCBA defect classification network. If it does not, we output its category probability; however, if it does, the discovery of the new category is facilitated by the hash code generated through another branch.

During the testing phase, samples with identical category descriptors are considered as clusters and sorted based on their sizes. We retain only the top-$|Y_Q|$ clusters while treating the remaining clusters as misclassified.

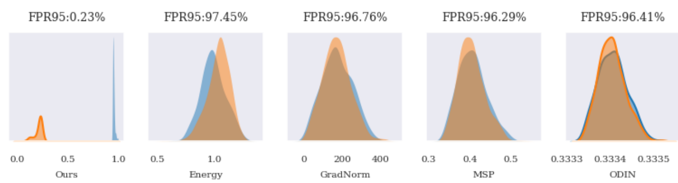
Table 1 Ablation studies on the form of different methods on different neural networks. We visualise the distributions of uncertainty scores w.r.t. to illustrate the superior performance of our employed methodology (see online version for colours)

network **Results of Different Methods**

resnet50



convnext_base



swin_t

cmts

Results. The impact of networks with different infrastructures on the discovery of new PCBA defect categories was presented in Table 3, and,we can observe that Swin-T, utilising transformer as its underlying architecture, achieves State-of-the-Art (SoAT) performance. Here we experiment with L varying from 64 to 8. The best performance is observed when the seen and unseen categories utilise distinct dimensions. The model exhibits enhanced performance in classifying unseen categories with smaller length of hash code. This can be attributed to the fact that as the hash code length decreases, the categorisable space(2^L) reduces, thereby leading to an increase in categorisation accuracy. However, since minimal change in overall accuracy, it indicates that the feature embeddings of the model possess robustness.

Table 2 Unveiling unseen defects: analysis of PCBA defect detection results. We present the performance evaluation of backbone networks trained on diverse base infrastructures. '↑' denotes superior values and '↓' preferable smaller values

	PCBA							
Methods	*FPR95*↓	*AUROC*↑	*FPR95*↓	*AUROC*↑	*FPR95*↓	*AUROC*↑	*FPR95*↓	*AUROC*↑
Ours	0.35	99.62	0.23	99.80	0.23	99.83	0.23	99.76
Energy	85.40	59.25	97.45	36.35	96.29	62.25	97.91	32.16
GradNorm	97.22	21.44	96.76	51.38	94.09	72.91	95.83	35.58
ODIN	95.94	24.82	96.41	51.82	95.25	64.77	96.52	34.73
MSP	96.41	24.52	96.29	52.05	93.28	64.32	94.09	46.32
	resnet50(2015)		**convnext_base**(2022)		**Swin-T**(2021)		**CMTS**(2021)	

Table 3 Comparison with diverse backbone: analysis of PCBA defect new category discovery results. New(the length of hash code) and the **ALL** accuracy is calculated at 8 hash code lengths

	PCBA					
Methods	*All*	*old*	*new(64)*	*new(32)*	*new(16)*	*new(8)*
Resnet50	85.61	90.17	70.35	69.71	71.26	72.33
ConvNext_base	87.83	92.77	70.69	68.72	70.78	71.69
Swin-T	87.02	91.38	70.73	70.33	71.06	72.73
CMTS	86.83	91.35	69.06	70.16	70.56	72.06

5 Conclusion

In this paper, we proposed a new and highly practical visual recognition problem termed on-the-fly new category of PCBA defect discovery. Meanwhile, we have also devised an intuitive approach to address the problem of discovering defect categories in PCBA. Furthermore, we enhance the model's adaptability by leveraging previously unencountered algorithms for detecting PCBA defects to improve the accuracy of recognising existing categories and employing unsupervised hashing for automatic discovery of new categories.

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