Resources, Conservation and Recycling,
Volume 177, February 2022, Article number 105963
DOI:10.1016/j.resconrec.2021.105963

Printed Circuit Board Identification Using Deep Convolutional Neural Networks to Facilitate Recycling

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Abstract. In this paper, we have proposed a robust Printed Circuit Board (PCB) classification system based on computer vision and deep learning to assist sorting e-waste for recycling. We have used a public PCB dataset acquired using a conveyor belt, as well as a locally developed PCB dataset that represents challenging practical conditions such as varying lighting, orientation, distance from camera, cast shadows, view-points and different cameras/resolutions. A pre-trained EfficientNet-B3 deep learning model is utilized and retrained for use with our data in PCB classification context. Deep nets are designed for closed set recognition tasks capable of classifying only the images they have been trained for. We have extended the closed set nature of deep nets for use in our open set classification tasks which require identifying unknown PCBs apart from classifying known PCBs. We have achieved an open set average accuracy of 92.4% which is state of the art given the complexities in the datasets we worked with.

Keywords: Deep Convolutional Neural Networks, Printed Circuit Board, Printed Electronic Circuit, PCB identification, Classification, Recycling

1 Introduction

With the advancements in technology, human lives are becoming increasingly reliant on electronic products such as computers, cell phones etc. Printed Circuit Boards (PCBs) which are composed of several Integrated Circuits (ICs) interconnected with each other through copper traces, lie at the heart of all these equipment. It is estimated that the electronic waste amounts to nearly 50 million tons per year [1] and the trend seems to be increasing by 7-10 percent each year. Some researchers have indicated that in the US alone, 500 million computers were discarded between 1997 to 2007 and over 1.2 billion phones are produced in a year worldwide [2]. Such huge quantities of electronic waste require highly efficient measures for waste management such that the environment is not severely affected.

To this end, in 2012 the European Union documented special directives for safe disposal and handling of waste electronics [3], and a special project called ReClaim was initiated to undertake research in finding efficient ways to recycle electronic waste [4]. The reviews undertaken in PCB recycling [5] [6] indicate that current recycling practices only allow recovery of 28% of the dominated materials and the remaining slug is either incarcerated or land filled. This is due to the fact that PCBs are highly heterogeneous in composition and it is very difficult to estimate the material composition of the PCB, which if known, would allow application of recycling processes appropriate to that composition.

The reason why precious metals could not be recovered is that e-waste which includes all sorts of electronics is not sorted and resultantly the proportion of precious metals compared to overall weight of the e-waste becomes so low that current industrial processes cannot recover them [1]. To enable recovery of precious metals, the e-waste containing higher amounts of these metals need to be identified and segregated. Manual sorting is tedious and not an efficient approach as the process is time consuming and costly. Therefore, we have proposed a vision-based method capable of identifying PCB models in waste streams thus enabling efficient recycling. If the model of a PCB is known, its precious metal composition from a database can accordingly be looked up.

Following are the major contributions of this paper:

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- We have proposed a deep learning based image classification method for PCB recycling process with higher performance.
- Inherently, Deep Convolutional Neural Networks (DCNNs) are designed for use in close-set classification context in which the query image must belong to one of the classes it has been trained for. We have extended and evaluated the closed set nature of deep nets to enable use of DCNNs in open-set classification tasks (i.e classifying unknown images apart from known/ trained classes).
- The proposed approach provides a pilot study using public as well as locally developed PCB dataset. The local dataset represents various complexities such as varying lighting, orientation, distance from camera, cast shadows, view-points and different cameras/resolutions.

2 Background Research

There are a number of works exploring the use of automated methods for electronic waste management in general. Weinert et al. [7] proposed an automated system for the classification of electronic waste using deep learning. Several researchers have implemented computer vision techniques specifically on PCB images. One of the application areas is automated optical inspection of PCBs in which methods to locate manufacturing related defects are identified. Indera et al. [8] used mathematical morphology and image processing tools to identify certain types of manufacturing defects to be used in automated inspection of PCBs in assembly lines. However, the application of computer vision techniques on PCBs for classification in a recycling context has emerged only recently. There have been two approaches to this problem. The first is aimed at identification of components such that recycling on component level is possible, and the second approach is related to PCB level identification where specified PCBs can be located in the waste stream.

2.1 Component Level Identification

Wei Li et al. [10] proposed an automatic PCB recycling pipeline which leverages several sensors including lasers, cameras and spectrometers for PCB material composition analysis. In [10] the authors have approached segmentation of PCB components using borders printed on PCB substrate around components, however this method may not apply to a wide range of PCBs as not all PCBs are designed with the said bordering features. As an extension of their work, Wei li et al. [11] proposed a technique to localize components on a PCB by clustering regions with similar set of features such as pixel intensity/ color information, texture and edges which were then used for background removal. In another relevant work [12], the authors attempted to read IC labels using Optical Character Recognition (OCR) and compared different OCR engine performance.

Overall, component level identification research is used for fine grained analysis aiming component level recycling and as a byproduct, the component composition can be used to identify the PCB as well. However, owing to large variation in PCB structures, finding a generic and robust solution which accomplishes component identification in practical scenarios is still an open research problem.

2.2 Complete PCB Identification

Another approach to facilitate recycling of PCBs was used by Pramerdorfer et al. [13] in which the authors proposed a method using local features of the PCB images augmented with homography verification to identify PCBs in a waste stream without having the need to extract component level details. Local features are a well-known technique used in object recognition. One of such effective feature extraction method known as Scale Invariant Feature Transform (SIFT) has been proposed by David Lowe [14]. The authors [13] have compared performance of various local feature matching methods such as SIFT, SURF, BRISK, FREAK and ORB. Accordingly, they have reported accuracy of up to

100% on a controlled pose and illumination dataset. The local features based method in [13] has its own strengths, nevertheless it is considered that following few limitations, if catered for, will be very helpful to advance research in this sub-domain:

- Little or no change of perspective is allowed between the query and database image. A study by Mikolajczyk et. al focusing on the performance of SIFT [15] shows that with 50 degrees variation in perspective between query and database image, the recall rate degrades to 24% and precision to 56%. Therefore, use of local features alone are not effective in datasets having perspective and illumination variations. An analysis of the dataset used by authors [16] reveal that test cases in which the test PCB is on the extremities of conveyor belt (introducing perspective distortions) have not been studied in which case the accuracy of the system may possibly reduce.
- The method at [13] requires heuristically calculated threshold values which although works well for the authors' dataset [16], though it may or may not be optimal for other scenarios.
- The authors [13] have proposed controlled lighting conditions using polarized and diffused light along with a polarization filter. Although such requirements are practicable and suffice for the scope defined by the authors, however it may be more practical to introduce methods which are invariant to lighting conditions.
- The method used in [13] is focused towards identifying PCBs which have exactly the same appearance. Thus, instead of a specific PCB, if it is desired to identify a generic class of PCBs such as Motherboard PCBs, Random Access Memory PCBs etc. which have a certain level of similarity in appearance but are not exactly same, then some modified and advanced solutions will be required.

In [9], the authors propose a system that performs PCB identification followed by defect detection with the goal of automating the process of PCB inspection. They have used SURF and ORB features to perform identification of PCBs. Once the PCB model is identified, the PCB image is transformed to match the reference image and the defect detection process is performed. This approach has similiar limitations as [13], as it also utilizes local features.

3 Objectives and Datasets

The objective of this paper is to propose a robust and generic solution for PCB identification in terms of the following:

- Invariant to reasonable changes in perspective/viewpoint as well as rotation. Thus, the test image does not have to be in the same perspective/plane as that of the reference (trained) image. This allows the freedom to use the training data from any source (such as from the internet, a facility or a customer etc.) not necessarily obtained from the same environment in which the testing is to be performed. Moreover, this feature would allow different recycling facilities to share datasets with each other, thereby allowing interoperability.
- Invariant to indoor and semi-outdoor conditions such that special polarized filters/ diffusers are no longer required. Ordinary lighting sources may suffice.
- Invariant to cast shadows in PCBs which are not very flat (e.g. PCBs fitted with heat sinks, connectors or unremoved parts of casing etc.).
- Invariant to motion blur.

A PCB dataset encompassing above mentioned variations was not available on the internet. Therefore, a dataset was locally developed consisting of 67 PCB classes under varying lighting conditions, camera viewing angles, blur effects, rotation and scale (i.e. PCB distance from camera). Each class in our datasets consists of a unique PCB model. By identifying the model of a PCB, we can obtain its composition from a database. In the recycling process, this data can be used to sort out PCBs that contain precious metals, so that they can be recovered. Samples from our dataset are shown in Figure 1 representing the above mentioned varying conditions.

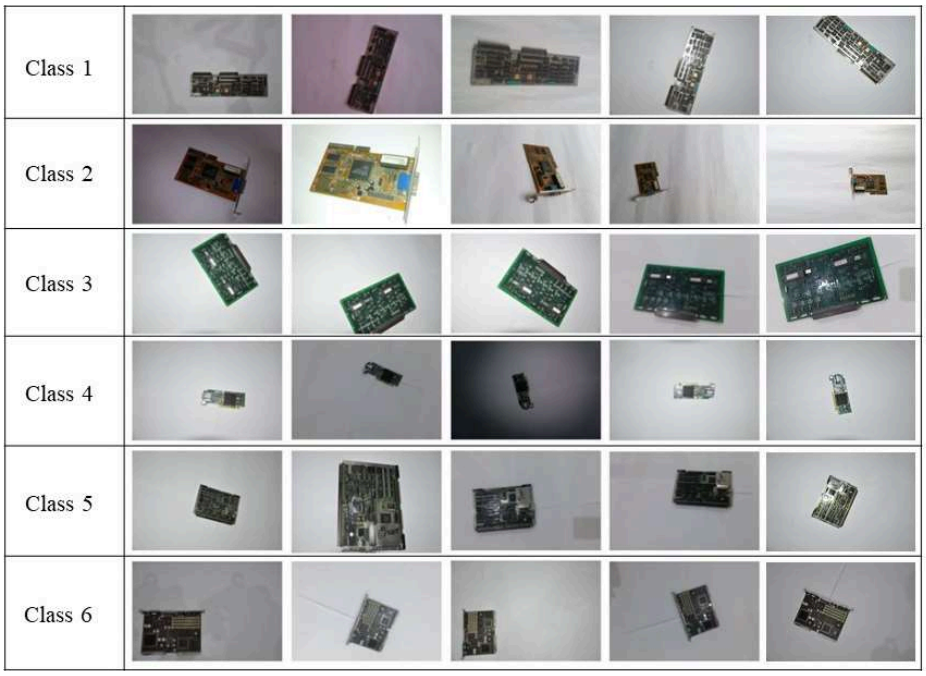


Fig. 1. Sample images from locally developed dataset. Each row represents varying pose and illumination variation for a class of PCB.

In addition to our own dataset, we have also used the PCB DSLR dataset [16], a public dataset consisting of 165 classes of PCBs acquired using a conveyor belt. A number of samples from this dataset are displayed in Figure 2. The information about the datasets is summarized in Table 1.

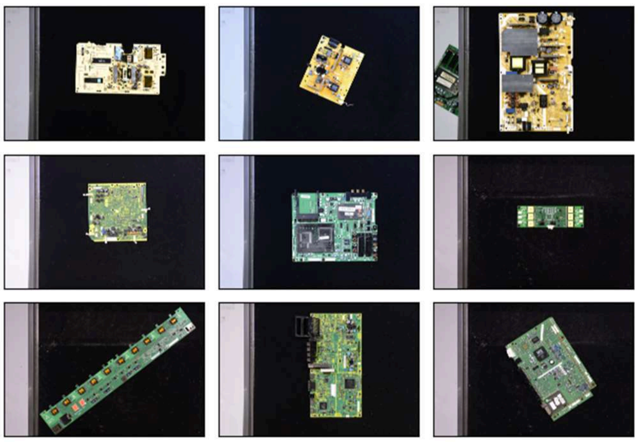


Fig. 2. Samples images from the PCB-DSLR dataset [16]

We have evaluated the performance of the chosen network on both the datasets separately as well as with a combined dataset with 232 classes of PCBs. We have performed two experiments i.e., closed set classification and open set classification. Closed set classification can be described as the ability of a classifier to label images known to belong to one of the classes it has been trained for, whereas in open set classification the classifier must also be able to distinguish the unknown images it has not seen before. For open set classification, we have added a special class to the combined dataset which contains random PCB images obtained from the internet using Google image search.

Table 1. Datasets used for experimentation

Model	Classes	Train Set	Validation Set	Test Set
Our Dataset	67	2222	684	361
PCB DSLR Dataset	165	418	165	165
Combined Dataset	232	2640	849	526

In order to compare the accuracy with the method proposed in [13], we have applied their method on our own dataset. We used a similar algorithm available at OpenCV [17] and modified it as per [13] using ORB features which gave a closed set accuracy of 100% on the dataset used by Pramerdorfer et al. [16] and only 60.9% on our data set. Therefore, in order to increase the classification accuracy on our data set we have approached the problem by using state-of-the-art Deep Convolutional Neural Networks.

4 Background - Deep Convolutional Neural Networks

Artificial Neural Networks (ANNs) are machine learning models which are inspired from the perceptron connectivity inside a brain. Deep Convolutional Neural Networks (Deep CNNs) are an extension of ANNs, except that they are deeper (typically tens of hidden layers) and instead of fully connected graphical structure, the neurons may be connected in convolutional layers. This allows performing filter operations on input images, where each filter has learnable weights acting as kernels. In Deep CNNs the neuron banks (filters) are three dimensional (RGB filters) i.e have height, width and depth. Moreover, unlike fully connected architectures, the neuron filters are connected to only a small subset of the previous layer therefore narrowing the receptive field. To cover the entire spatial space, convolution shift operation is performed. A convolution layer can have many filter kernels and the output of all filters in a layer are concatenated horizontally to form a 3D cube. CNNs have been around for many decades but their power was underestimated until back propagation was used for training neural networks in 1998 when Lecun et al. [18] used CNN (LeNet 5) for document recognition. However, the question if this gradient based back propagation technique would scale up to larger CNNs lingered on until in 2012 when a deep CNN was used to classify ImageNet data set [19] with a top-5 error rate of 16.4% which was remarkable. Later, other variations were developed with several improvements and as of today, deep CNNs have achieved a top 5 classification error rate as low as 1.2%.

A brief overview of the EfficientNet Model and Transfer Learning methodology, used in this work for the PCB classification problem, is given in the following paragraphs.

4.1 EfficientNet

Tan et al. from Google inc. have proposed a novel model scaling method that improves performance by scaling in all dimensions of scale, width, depth, and resolution using a compound coefficient. In addition to demonstrating the effectiveness of this scaling method on ResNet and MobileNet, the authors have also developed a new family of Deep CNN architecture known as EfficientNet [20] which achieved a top-1 accuracy of 84.3% on ImageNet dataset [19] at the time of its publication in 2019. The related details are provided in Table 2.

Table 2. EfficientNet Models

Model	ImageNet Top-1 Accuracy	Parameters
EfficientNet-B0	77.1%	5.3M
EfficientNet-B1	79.1%	7.8M
EfficientNet-B2	80.1%	9.2M
EfficientNet-B3	81.6%	12M
EfficientNet-B4	82.9%	19M
EfficientNet-B5	83.6%	30M
EfficientNet-B6	84%	43M
EfficientNet-B7	84.3%	66M

4.2 Transfer Learning

Training Deep CNNs is a challenging task. The foremost problem is the amount of data required to train a deep CNN to achieve a desired level of classification accuracy. Though there is no one answer to the size of dataset required to attain a required classification accuracy in a specific application. Razavian et al. [21] reported that a deep CNN can be used for classification of any arbitrary dataset by using feature extraction layers pre-trained on any other (large) dataset. In this way, the convolution layers which have attained the capability of extracting powerful features can be fixed while the last few layers can be re-trained as per the problem at hand. This methodology has since been widely used in deep learning based applications and is commonly referred to as Transfer Learning [22] [23] [24]. In our case, we had a combined dataset of ~4,015 images with 232 classes. Similarly, we have used transfer learning considering the broader spectrum and related environmental and operational dynamics involved in the PCB recycling facilities.

5 Closed Set PCB Classification using EfficientNet-B3 Inception Model

We leverage transfer learning for our application, using a pretrained EfficientNet-B3 model trained on ImageNet. We have chosen the EfficientNet-B3 model for a decent tradeoff between accuracy and inference speed. We first froze the pretrained model, removed the top layer, and then used it as a feature extractor to train a classifier for 80 epochs. This is followed by unfreezing the top 20 layers and then fine-tuning the network for 50 epochs. We have repeated this process for both the datasets separately as well as on the combined dataset. The experiments were performed using the Tensorflow Keras framework [25].

Some of the important parameters set for training are as follows:

- Data augmentation: Random rotation, random flip
- Batch Size: 32
- Learning rate (Transfer learning): 1e-2
- Number of epochs (Transfer learning): 80
- Learning rate (Fine-tuning): 1e-4
- Number of epochs (Fine-tuning): 80

After 80 epochs of transfer learning, we unfreeze the top 20 layers and fine tune the network for another 80 epochs. This increases the validation accuracy for all three datasets. The training/validation accuracies for training are shown in Figure 3.

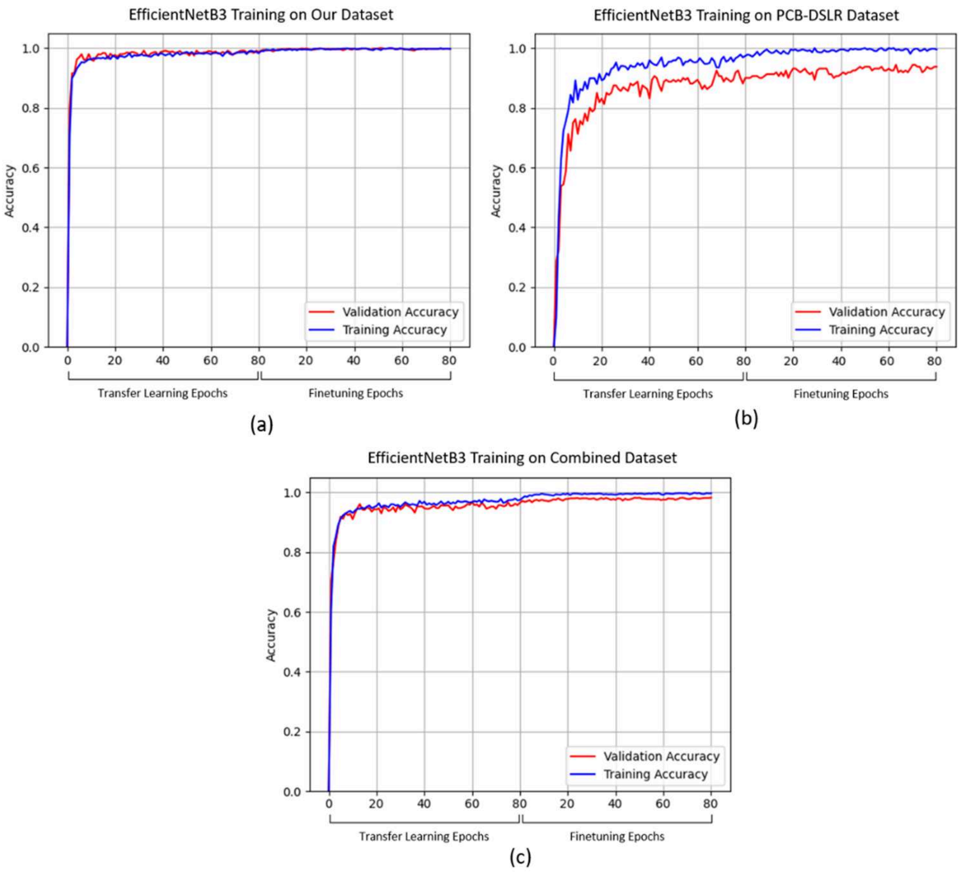


Fig. 3. Transfer learning and finetuning validation accuracy on (a) Our dataset; (b) PCB-DSLR dataset; (c) Combined dataset

The accuracies obtained after both stages of training on all three datasets are summarized in Table 3.

Table 3. Validation and test accuracies obtained on training EfficientNet-B3

Dataset	Validation Accuracy	Test Accuracy
Our Dataset	99.85%	100%
PCB DSLR Dataset	94.37%	90.30%
Combined Dataset	98.19%	95.81%

We have also evaluated the comparative performance of EfficientNet B2, B3 and B4. The EfficientNetB4 model produced the best validation and test accuracy scores, outperforming EfficientNetB3 and EfficientNetB2. The results obtained are shown in Table 4.

Table 4. Validation and test accuracies obtained on training EfficientNet-B3

Model	Train Accuracy	Validation Accuracy	Test Accuracy
EfficientNetB2	99.31%	97.95%	94.29%
EfficientNetB3	99.65%	98.19%	95.81%
EfficientNetB4	99.69%	99.03%	98.09%

6 Open Set Classification Experiments

The above-mentioned setup was aimed at ascertaining the closed set recognition performance. However, in real world classification such as in our case, the classifier must also be able to distinguish the unknown images it has not seen before. The test accuracy achieved on combined dataset in closed set classification sets the benchmark (in our case 95.81%) which cannot be exceeded in open set classification. Using Deep CNNs for open set classification is a matter of current debate and several authors have proposed methods to recognize unknown classes [26] [27]. In [28] the author proposed using Weibull-Calibrated Support Vector Machine which seemed to work well compared to other classification methods. In [29] the authors proposed a technique to adapt Deep Nets for open set recognition by placing an additional layer called Open Max. This layer took input from the layer before softmax and used these scores to identify unknown images. Based on these ideas, we have experimented and compared four different methods on the combined dataset to achieve open set recognition as described below.

6.1 Training CNN for Negative Class

This technique is based on addition of a Negative Class (we labelled as NAN) in closed set training of the CNN. We took random images of PCBs not part of any other class being trained and included a NAN class in the training data set. The intuition was that if we train a CNN for a separate class with different images not belonging to any other class, the final layer before softmax will output nearly uniform distributions of scores during training with no resembling patterns and may remain confused. Taking leverage of this confusion it might be possible for this neuron to learn what the test image of an unknown PCB will output. A block diagram depicting the proposed architecture is shown in Figure 4.

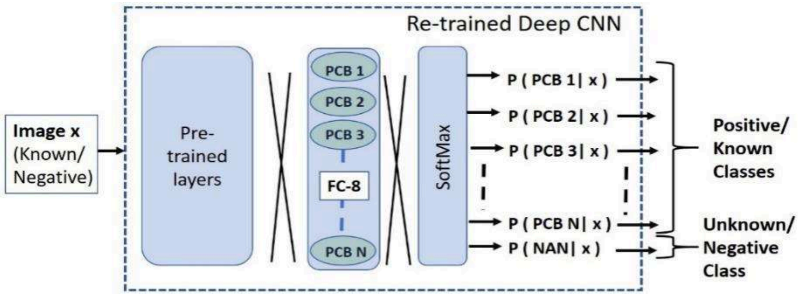


Fig. 4. Deep CNN with a negative class

The model was retrained using the combined dataset as described in the previous section (closed set training) except an additional Negative Class was added. The retraining successfully converged, and a validation set accuracy of 98.72% was achieved as shown in Figure 5. The final test stats using a test set consisting of 544 images (i.e 526 + Negative class) achieved an open set average accuracy of 92.4% as shown in Column 1 of Table 5.

One important consideration using this method is that the Negative Class should not only include a variety of PCB images but also a variety of backgrounds. In our case, the Negative Class was composed of approximately 55% images taken in a background similar to known classes of our own dataset, whereas 45% images were from other backgrounds. Although we have only tested one composition of Negative class, but we expect the accuracy (especially the True Negative rate) to slightly vary as this composition is changed.

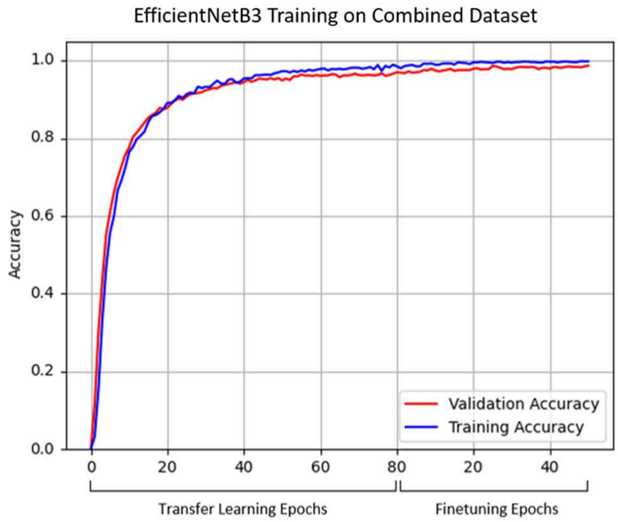


Fig. 5. Transfer learning and finetuning validation accuracy for open set classification task

6.2 Adding Auxiliary Classifier

The other approach that we have experimented involves training the CNN for closed set recognition and augment it with an additional binary classifier on top of the CNN, which separates known and unknown classes. During classification, if the auxiliary classifier outputs 'unknown/ Negative class' then it is assigned as such and if known class is ascertained, then the class with maximum probability output from Deep CNN is assigned. The overall operation is depicted in Figure 6. Since the task of auxiliary classifier is binary classification, a correct merit of accuracy would entail equal test cases of both classes. However, since we have disproportionate positive and negative examples in the test set, we have averaged the accuracy as follows:

$$Accuracy = 0.5 * \frac{TP}{TP + FN} + 0.5 * \frac{TN}{TN + FP}$$

Where TP = True Positives, FN = False Negatives, TN = True Negatives and FP = False Positives.

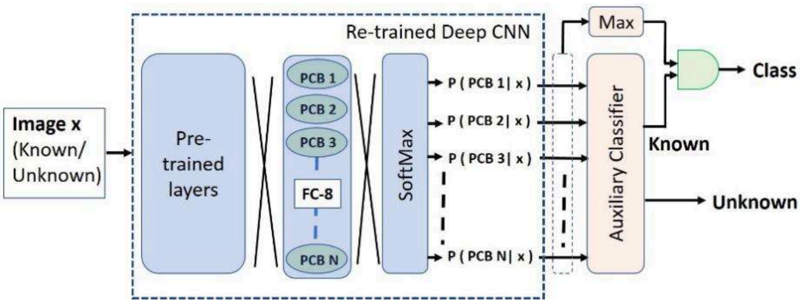
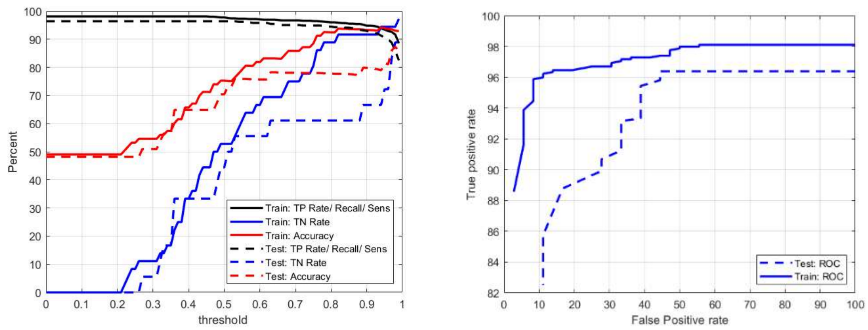


Fig. 6. Overall system operation with auxiliary classifier

The three different classification techniques we have experimented using auxiliary classifier are described below:

6.2.1 *Method 2: Thresholding Probability*

A trained CNN outputs the probabilities with which a test image matches with the trained classes. The class with the highest probability value is selected as the most probable match and the value of probability P_{max} indicates the confidence of classification. We have first experimented thresholding P_{max} value such that if P_{max} exceeded certain threshold, we considered the top choice as output label otherwise 'No Match' label was assigned. The optimal threshold value was ascertained from the validation set (used in Deep CNN re-training) using accuracy curves as shown in Figure 7(a) and validated using Receiver Operating Characteristics (ROC) curve Figure 7(b) which shows that the maximum accuracy of 94.15% is achieved at 0.94 threshold value. We have applied this threshold on the test set and the final test accuracy of 78.96% was achieved. The performance statistics are shown in Column 2 of Table 5.

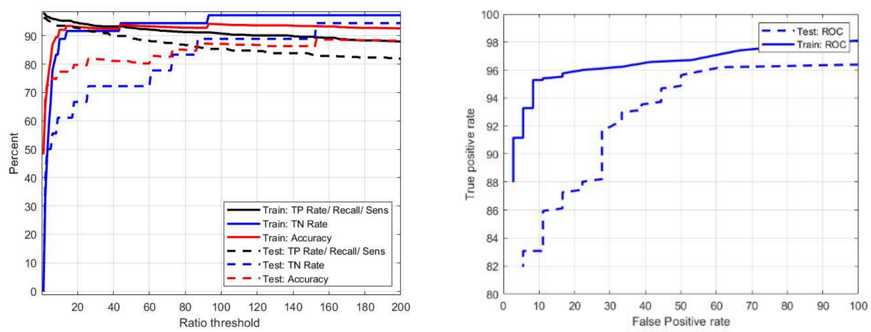


(a) (b)

Fig. 7. Auxiliary Classification using threshold at Max Probability (a) Performance curves with varying threshold during training and testing (b) ROC Curve: training and testing

6.2.2 *Method 3: Thresholding Probability Ratios*

While highest class probability value is an absolute term, the ratio $R_p = P_{max}/P_{max-1}$ between highest class probability P_{max} and the second highest class probability P_{max-1} contains more information such as the relative distance which will be high for confident decisions and low otherwise. As an example, suppose that for a given test image, the Deep CNN assigns highest probability (say 0.49) to the true class, but it is less than the set threshold of 0.5 and is rejected. Even in such a case, if P_{max-1} is very low (say 0.05) compared to P_{max}, one can still infer that the class indicated by P_{max} is the correct class. We have therefore studied the system accuracy by setting the auxiliary classifier to threshold R_p and the results are shown in Figure 8. The maximum training accuracy of 94.19% was achieved (using the same data used in Method 2) at R_p = 93. The test accuracy (on the test set) was 87.22% as shown in Column 3 of Table 5 which is significantly higher compared to the previous methods.

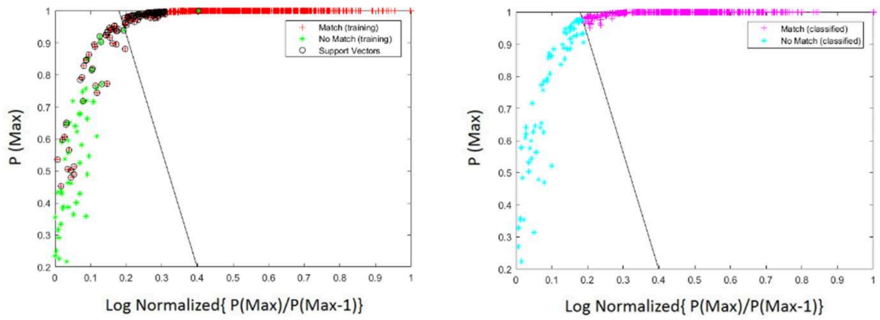


(a) (b)

Fig. 8. Auxiliary Classification using threshold at Probability ratio (a) Performance curves with varying threshold during training and testing (b) ROC Curve: training and testing

6.2.3 *Method 4: SVM Classifier*

The final approach was to leverage on both the above parameters i.e P_{max} and R_p and train a classifier in 2-dimensional feature space. We have opted for Support Vector Machine (SVM) for this purpose. It may be noted that the ratio $R_p = P_{max}/P_{max-1}$ has the tendency to attain large values as $P_{max-1}\ to\ 0$. Therefore we have converted R_p to log scale and restricted the maximum value (C) it can attain by using the relation $R_p = Log[\min\ (P_{max}/P_{max-1}, C)]$ with (C) arbitrarily set to 5580. Figure 9 shows a plot of feature space where it can be noticed that the data is not completely separable. This method yielded an accuracy of 80.50% on the test set. The performance stats of this method are given in Column 4 of Table 5.



(a) (b)

Fig. 9. SVM training and classification feature space (a) SVM training on a subset of Training Data (b) SVM classification on the test set; for clarity Rp has been normalized to 1

6.3 Open Set Classification Summary

The results of above-mentioned methods are summarized in Table 5. Training Deep CNN for a negative class (Method 1) achieved highest accuracy, however the TN rate contributes lesser and TP contributes higher to the overall accuracy. In a PCB recycling facility this would mean that most of the desired PCBs could be identified at the cost of slight increase in the number of unwanted PCBs. Thresholding probability ratio (method 3) resulted in the same TN rate, but lower average accuracy.

Table 5. Performance Stats Summary of Open Set Classification

Performance Measure	CNN with NAN Class	Thresholding at Pmax	Thresholding at Rp	SVM
Avg. Accuracy	92.4	78.96	87.22	80.50
TP Rate / Recall / Sens	96	91.3	85.6	88.8
FP Rate	11.1	33.3	11.1	27.8
TN Rate	88.9	66.7	88.9	72.2
FN Rate	4	8.7	14.4	11.2
Precision	99.6	98.8	99.6	98.9

7 Conclusion and Future Directions

In this paper, we have proposed a robust PCB classification system based on Deep Convolutional Neural Networks to assist sorting e-waste for recycling. We have presented different ways to use Deep CNNs for PCB classification in an open set context and achieved an accuracy of 92.4% for open set classification, which is state of the art given the complications in the dataset we have worked with. The proposed PCB classification system can be adapted and deployed in recycling facilities to sort PCBs for efficient recycling of precious metals, reducing the amount that is incarcerated or landfilled. Our method for PCB classification is implementable in a practical environment. However, the only advantage that local feature matching techniques have over our method is that only one reference image is required for training whereas in our case, approximately 30 different reference images per class are required so as to train Deep CNN without overfitting. On the brighter side arranging 30 images may not be very difficult since there are no restrictions on background, lighting, camera, orientation, perspective, distance from camera and should be possible in only a couple of minutes. Nevertheless, there are Deep CNNs that use even lesser number of reference images for training such as One-Shot Learning Siamese Networks [30] which can be experimented for this problem.

The scope of this paper has been limited to identifying specific PCBs, however our method can be used to identify a generic class of PCBs (such as Motherboards, RAMs etc.) that has some level of similarity in appearance without having to train for every expected variation. Our initial findings confirm this claim though a more focused study can be carried out as a future work. Moreover, Deep CNNs can also be utilized for component level detection and identification and can generate more information from the PCB image allowing more efficient recycling.

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2021-10-25

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Soomro IA, Ahmad A, Raza RH. (2022) Printed circuit board identification using deep convolutional neural networks to facilitate recycling, Resources. Conservation and Recycling, Volume 177, February 2022, Article number 105963

https://doi.org/10.1016/j.resconrec.2021.105963

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