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Binary and Multi-label Defect Classification of Printed Circuit Boards based on Transfer Learning

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Abstract. Automatic optical inspection for printed circuit boards (PCB) is an important step to assure quality control in electronic manufacturing. Recently deep learning models have been used to detect and classify PCB defects. Since public PCB datasets usually are not large enough to train deep models from scratch, transfer learning has proved to be an effective strategy to overcome this limitation. In this paper we evaluate the influence of input image size for non-referential binary classification of PCB images from the DeepPCB dataset and moving further we evaluated a multi-label classification, both based on transfer learning. The best models achieved 99.5% accuracy for binary classification and mean accuracy of 95.16% for multi-label classification.

1 Introduction

In order to assure quality control in electronic devices, automated optical inspection is an important step to detect defects in printed circuit boards (PCB) [1]. There are three main tasks in automatic optical inspection for PCBs: (i) binary defect classification, (ii) multi-label defect classification and (iii) defect location. While the first task is about to classify a PCB as defective or not, the second classification task also aims to identify the defect type. Since a PCB can present multiple defects types, the second task can be seen as a multi-label classification problem [2].

There are two main approaches for PCB automatic optical inspection: referential and non-referential methods [1]. The referential method is based on a comparison between two images: the reference image and the test image. Referential approaches have issues regarding miss-alignment and illumination differences between reference and test images, although it usually has higher accuracy scores than non-referential approach [3].

The non-referential approach initially was concerned with design rule verification (such as track width and distance between elements) using standard

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digital image processing techniques [4]. With the advances in machine learning and most recently deep learning models, non-referential approach has been researched for general defect detection and classification [2, 5].

Transfer learning has been proved as an effective strategy to overcome the limitation of available data to train a deep model from scratch [6, 3]. Besides that, when a pre-trained model is used for transfer learning, the input image size can be different from the original size used to train the model. This happens because the convolutional layers (whose knowledge is transferred) accepts different shapes in its input. Using a non-referential approach, this work aimed to evaluate the input size image influence on accuracy and complexity model (observed as the number of parameters in the model) for binary classification in the DeepPCB dataset using transfer learning and fine-tuning based on the pre-trained VGG16 model. We also evaluated a multi-label classification model, based on transfer learning as well.

2 Related works

Takada *et al.* [5] proposed a non-referential method for defect detection and classification with SURF algorithm to extract a defect candidate region which feeds a convolutional neural network (CNN) followed by a SVM classifier. Using the same dataset, Gosh et. al. [3] used mid-level features of a pre-trained Inception V3 model to classify PCB images into true defects (fatal defects) or pseudo defects (defects which can be corrected). Zhang *et al.* proposed a multi-label classifier with a CNN model addressed as multiple binary classifications [2]. The CNN model has three convolutional layers followed by two fully connected layers.

Tang *et al.* [7] published the DeepPCB dataset and a deep model using a referential approach for defect classification and location. This deep model uses a pre-trained model (VGG-tiny) to extract features from template and test image and feed a group pyramid pooling module followed by a prediction layer. This model achieved 98.6% of mAP (mean average precision).

Considering referential approach issues, Silva *et al.* proposed a transfer learning based model for binary classification of the DeepPCB dataset using non-referential approach[6]. This model achieved 89% of accuracy and the authors conclude that shallower models perform better on DeepPCB images, since those images do not present complex textures and color information.

3 PCB Defect Classification Model

Transfer learning is a strategy to transfer knowledge from one domain or task to another domain or task [8]. In the deep learning field, transfer learning is a strategy to harness the general features learned from a model trained for a particular task and apply them in another task [9]. It usually requires replacing the final layers of the pre-trained model. The image classification and object detection has been solved by CNN's, and transfer learning has shown a different solution for smaller training datasets [3]. The VGG16 network [10] pre-trained on the ImageNet dataset is used for evaluation of the increasing networks depth, and its weights are transferred to solve the classification of PCB images problem.

Following the standard transfer learning strategy [9], the top layers of the pre-trained VGG16 [10] are removed, as shown in Figure 1. The new classifier used consists of two fully connected layers of 512 units with ReLU activation and 0.3 dropout regularization [6]. The final classification layer has one sigmoid unit for binary classification or six sigmoid units when used for multi-label classification (one unit for each class). Moreover, we used the RMSProp optimization algorithm with 10^{-5} learning rate and binary cross-entropy loss. Moreover we also used online image data augmentation with geometric transformations as vertical/horizontal flip and rotation [11].

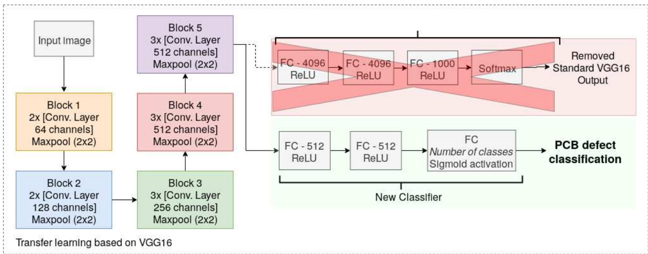

Fig. 1: Transfer learning strategy based on VGG16 Model.

Regarding binary classification, two different input image sizes were used: the default input size of the VGG16 (224x244) and the size of the images provided by the DeepPCB dataset (640x640), further referenced by the full image size.

Based on [6] that found shallower models presented better accuracy in binary classification in the DeepPCB dataset, for each input size the following experiments were performed for binary classification:

1. The classifier's layers were connected after block 5 of the pre-trained model VGG16, as shown in Figure 1, and the last two convolutional blocks (4 and 5) were fine-tuned;
2. The classifier's layers were attached after block 4 of the VGG16 pre-trained model, that is, block 5 was removed. Also, the two convolutional blocks before classifier (blocks 4 and 3) were fine-tuned;

For multi-label classification, each one of the six output units is responsible for classifying each defect type, working as multiple binary classifier with binary cross-entropy loss. We used the best topology in binary classification experiments to evaluate multi-label classification.

4 Experimental results

The experiments were done using the DeepPCB dataset [7], which has 3000 images, of those 1500 are template images (without defects) and 1500 are test images (with one or more defects , Figure 2). Then we applied two methods: a binary classification [6] and a multi-label classification problem [2].

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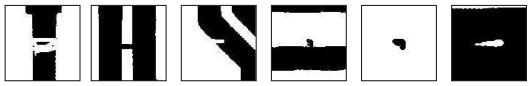

(a) (b) (c) (d) (e) (f)

Fig. 2: Defect classes cropped from the DeepPCB dataset: (a) open, (b) short, (c) mousebite, (d) spur, (e) copper and (f) pin-hole.

4.1 Results for binary classification

The results (mean of top 5 models) of accuracy and F1 score for the binary classification on the DeepPCB dataset are showed in Table 1. The model with all convolutional layers of pre-trained VGG16 (block 1 to block 5 in Figure 1) and last two convolutional blocks fine tuned achieved 99.5% of accuracy on the test set with 119,835,969 parameters (this model is referred as VGG16 block 5). It can be seen the decrease of the accuracy with the reduction of VGG16 convolutional layers, except when the input image size is 150x150.

Input size	**Metrics**	**Models**	
		VGG16 Block 5	VGG16 Block 4
150 x 150 (Results from [6])	Accuracy	83.6%	88.5%
	F1 Score	0.811	0.879
	Number of param.	19,172,673	29,132,609
224 x 224	Accuracy	95.8%	92.9%
	F1 Score	0.958	0.928
	Number of param.	27,823,425	59,279,169
640 x 640	Accuracy	**99.5%**	98.6%
	F1 Score	**0.995**	0.984
	Number of param.	**119,835,969**	427,329,345

Table 1: Results for binary classification for Fine Tuned models with different size input images (input image size 150x150 were reproduced from [6]).

Since convolutional blocks followed by max pooling layer reduces the output dimensions of network, less blocks implies in bigger feature maps to feed the fully connected layers. The fully connected layers are responsible for most parameters of VGGs based models. Because of this, for input image size of 640x640, removing the block 5 of VGG16 increase the number of parameters in 3.57 times (from 119,835,969 to 427,329,345 parameters).

From 1000 PCB images in test set, VGG16 block 5 model misclassified the five images shown in Figure 3. For Figures 3 (a) and (b), the model reported a false positive. The false positive for these particular images may be related to the presence of numbers (3-087 can be seen in those images). Those numbers can be confused as shorts, open or even cooper defects since it does not make part of a regular circuit track. Exploring the training set we found sixteen examples of PCB images containing text or numbers being six defective and ten not defective.

Figures 3 (c), (d) and (e) are false-negative errors. Figure 3 (c) has two short

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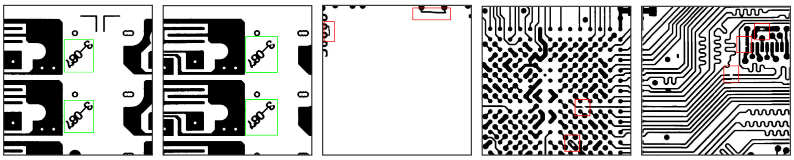

(a) (b) (c) (d) (e)

Fig. 3: The five missclassified images by VGG16 block 5 model with full image input size (frames were added to each image).

defects according to the corresponding annotation file. Those short circuits can be visualized as the two non-uniform tracks in top right and top left. Even for human inspection, shorts defects are hard to be found without a referential image, because the short can also be part of a PCB project. The images from Figure 3 (d) and (e) present more complex patterns to evaluate, although human inspection can easily find an open-circuit defect in both images.

4.2 Results for multi-label classification

The individual results (mean of top 5 models) are showed in Table 2 with Accuracy and F1 score metrics. Besides that, the general results our non-referential model are 0.952 of precision, 0.951 recall and 0.951 F1 score, while the best results found by Tang *et al.* using a referential approach are 0.982 precision, 0.981 recall and 0.982 F1 score, regarding that this approach requires the template image for testing a PCB. Our proposed model achieved 95.1% of average accuracy with the highest accuracy in open class (96.6%) and the lowest in mousebite class (92.4%).

Exploring the DeepPCB dataset, defective images usually have multiple types of irregularities. Only five examples have a single class and most of them have at least three types of defect. This dataset characteristic causes some classes being high correlated to other defects.

Class	Open	Short	Mousebite	Spur	Cooper	Pin Hole
Accuracy	96.6%	96.4%	92.4%	92.6%	96.4%	96.4%
F1 Score	0.966	0.964	0.924	0.926	0.964	0.964

Table 2: Results for each defect in multi-label classification.

5 Conclusion

The most recent advances in deep learning has brought attention to increase the performance of automatic optical inspection for PCBs. We used a non-referential approach based on transfer learning to evaluate if a PCB is defective (binary classification) and which are the PCB defects (multi-label classification).

For binary classification we evaluated two input images sizes: the standard VGG16 input size (224x224) and the default image size from the DeepPCB dataset (640x640). We also evaluated different depth by removing convolutional

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blocks of VGG16. We noticed the input image size as an import factor since previous work reported 89% accuracy with input image of 150x150 pixels [6]. In this work we used the full size input images and achieved an accuracy of 99.5% with all convolutional blocks of pre-trained VGG16. It is worth mentioning that increasing the input image size also increases the number of parameters of the model, given that feature map extracted from convolutional layers increases as well as showed in Table 1.

Regarding the multi-label classification, using the same structure of binary classification model replacing only the final classification layer, the mean accuracy was 95.1% and the lowest accuracy achieved was 92.4% for the mousebite defect. Using non-referential approach our model achieved neighbouring results to the ones presented by Tang *et al.* with a referential approach. Since the non-referential approach requires less information then the referential ones, our model is very competitive in face of the solutions using referential approaches because it can overcome issues such as miss-alignment and illumination sensitivity in a real production application.

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