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# A Deep Learning-based Microsection Measurement Framework for Print Circuit Boards

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***Abstract*—Microsectioning is a destructive testing procedure used in the printed circuit board (PCB) fabrication industry to evaluate the quality of PCBs. During cross-section analysis, operators measure PCB component widths manually, which can lead to inconsistencies and make it challenging to establish standardized procedures. We propose a Deep Learning-based Microsection Measurement (DL-MM) Framework for PCB microsection samples to address this issue. The framework comprises four modules: the target detection module, the image preprocessing module, the labeling model, and the coordinate adaptation module. The target detection module is responsible for extracting the area of interest to be measured, which reduces the influence of surrounding noise and improves measurement accuracy. In the image preprocessing module, the target area image is normalized, labeled with coordinates, and resized to different sizes based on the class. The labeling model utilizes a convolutional neural network (CNN) model trained separately for each class to predict its punctuation, as the number of coordinates varies for each class. The final module is the coordinate adaptation module, which utilizes the predicted coordinates to draw a straight line on the expected image for improved readability. In addition, we evaluate the proposed framework on two types of microsections, and the experimental results show that the measurements' root-mean-square error (RMSE) is only 2.1 pixels. Our proposed framework offers a more efficient, faster, and cost-effective alternative to the traditional manual measurement method.**

***Index Terms*—Microsection measurement, print circuit boards, deep learning**

## I. Introduction

Microsectioning is one of the primary quality analyses of printed circuit boards (PCBs). This technology enables the PCB manufacturing industry to inspect the interior of PCBs and make precise measurements, allowing for thorough quality control of the production process and assurance of PCB quality [1]. Unfortunately, we cannot demonstrate the actual dataset due to privacy policy restrictions. However, we have reconstructed representative images of two types of PCB micro-sections, the substrate and copper, which are illustrated Fig 1. The primary objective of microsection inspection is to ensure the quality of various aspects of PCB, including the base material, inner structure of multilayer boards, and connections between different layers. The microsectioning process typically involves five main steps: 1) Selecting an appropriate PCB, 2) Cutting out a piece as a sample, 3) Embedding the sample in resin, 4) Grinding the sample to a flat surface, and 5) Manually measuring the component widths by using a microscope. Manually measuring the component widths on the PCB board is necessary to check PCB quality. This leads to variations in measurements between individuals and reduced production efficiency. However, AI-assisted inspection [2] can reduce labor costs and increase yield while maintaining quality. This method provides significant economic benefits for PCB manufacturers.

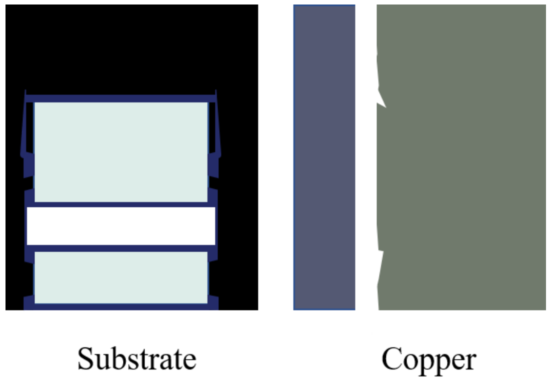


Fig. 1. PCB microsection images.

This paper presents a Deep Learning-based Microsection Measurement Framework that leverages a small dataset comprising two types of PCB slices to train a landmarking model with a low error rate. The proposed framework consists of four modules: the target detection module, the image preprocessing module, the labeling model, and the coordinate adaptation module. In the target detection module, we crop the feature area in the image as our ROI image. The subsequent operations are only processed for this ROI image, effectively reducing the surrounding noise and the error rate of the follow-up operations.

In the image preprocessing module, we normalize the value range of the image and resize it into different sizes according to the different labeling models for each slice. Additionally, we designed two distinct labeling models using a four-layer CNN architecture in the labeling module to address the challenges of uneven and limited data for each slice. Finally, the coordinate adaptation module processes the predicted coordinates and draws line segments on the image to indicate the component width. The experiments showed that our framework successfully reduced the RMSE of substrate measurement to less than three.

## II. Related Work

Using deep learning have higher accuracy for landmark technology. In [3] [4], the methods of PCB defect detection in recent years have been reviewed. [5] presented a robust framework for localizing key landmark points to extract the iris more accurately. In [6], a total of points on the human face's eyes, nose, and lips were predicted. The authors proposed a cascaded convolutional network where several different convolutional neural network stages are sequentially connected to predict the final face landmark. There were three levels in the cascaded convolutional network. There are three CNNs in level 1. The first is used to predict five points, the second is used to predict the eyes and nose, the third is used to predict the sides of the nose and lips, and finally, averaging all the obtained coordinates, the initial estimated position of five points is obtained. The next level 2 is to use two CNNs for each coordinate to more accurately predict its coordinate position and the method of level 3 is similar to that of level 2, so the final result is coarse to fine. Level 1, to initialize critical points on the image, it is deeper than the models of level 2 and level 3. The first layer in the union architecture uses a convolutional neural network, so it has a robust feature extraction ability and solves the critical point initialization problem of the traditional face labeling technology like Active shape model(ASM) [7] and Active appearance model(AAM) [8].

In [9] was to use the improved ASM to identify the key landmarks of the PCB and improve the accuracy. In [10], this article mainly predicted 68 critical points on the face. The method was similar to [6]. They were made using the union architecture, but before the input of the first layer of the model, CNN was used to predict the face's bounding box. So the accuracy of level 1 positioning was much improved.

In [11], image processing techniques such as the Perona-Malik filter and binary segmentation were also utilized to perform width measurement of surface cracks on fiber-reinforced earthen construction materials. The authors also performed skeletonization to obtain the central points of the cracks, followed by the k-means algorithm to determine the width of the profile line to be the width of the surface cracks. In [12], the author proposed a DL-enabled quantitative crack width measurement method. Detect cracks in complex scene images with high accuracy using a dual-scale convolutional neural network in the detection stage.

In [13], the author used U-Net for segmentation to locate ventricles and atria in cardiac MRI. U-Net can predict the probability of each pixel becoming a landmark and output a heat map representing the landmark results. In [14], the authors used U-Net and global adaptive average pooling to predict landmarks on X-ray images. Since the global adaptive average pooling only speeds up the training, but the accuracy is not high, the global adaptive average pooling is replaced with a fully connected layer with dropout to improve the accuracy. The authors then used transfer learning to transfer each landmark on the graph to each model since the features of each landmark should be similar. The above process provided more fine-grained predictions for the entire architecture. In [15], the authors of this paper applied U-Net and DeepLabV3+ for river identification and subsequent width measurement. The estimated width was compared with the manually measured width, and the results showed a significant improvement in accuracy compared to existing river width measurement methods.

## III. Deep Learning-based Microsection Measurement Framework

Fig. 2 is the architecture of the Deep Learning-based Microsection Measurement Framework (DL-MM). DL-MM consists of four modules: the target detection module, the image preprocessing module, the labeling model for labeling coordinates using a convolutional neural network, and the coordinate adaptation module. In this section, we will discuss each of these modules separately.

### A. Target Detection Module

The target detection module focuses on marking a small part of the sliced image while eliminating unnecessary noise that occupies most of the area. As the given dataset is sparse, we aim to prevent image noise from affecting the model's error rate and to help the model capture relevant features. We use the You Only Look Once version 5 (Yolov5) model to locate the input image and capture the Region of Interest (ROI) image in this module. This approach allows the detection to focus on the target and avoid other noise on the image, which could interfere with the training of the labeling model and negatively impact the model's accuracy. Our dataset consists of two types of slices: substrate and copper. The result is shown in Fig. 3.

### B. Image Preprocessing Module

In the image preprocessing module, we first normalize the size of the image. Depending on the type of PCB slice, the region of interest (ROI) of the original image may vary and have different aspect ratios. For example, the ROI image obtained by the substrate may have a much longer length compared to its width, which is different from the ROI image obtained from the copper. Scaling all images to the same size may result in losing essential features and increase the model's error rate. Therefore, resizing the images based on the different PCB slice types is necessary.

### C. Labeling Model

In the labeling module, we need to predict different coordinates and image sizes for each type of PCB slice. Due to the insufficient and uneven dataset, we avoided using the same model for each type, as it could result in higher error rates. Instead, we designed independent models for each type to ensure the highest accuracy for each dataset. However, the parameters of each model are the same, with only the input and output layers changed accordingly.

Our labeling model is a convolutional neural network model consisting of four convolutional and pooling layers, as depicted in Fig 4. The numbers above each layer indicate the number of filters used. Each layer consists of two convolutional layers and one pooling layer, with the kernel size of the convolutional layer set to $3 \times 3$ and the pooling layer set to $2 \times 2$. We use ReLU as an activation function for each convolutional layer. The fully connected layer at the end of the model also uses ReLU as the activation function. In contrast, the output layer does not use any activation function, as the coordinate values are continuous and fall within the image size range.

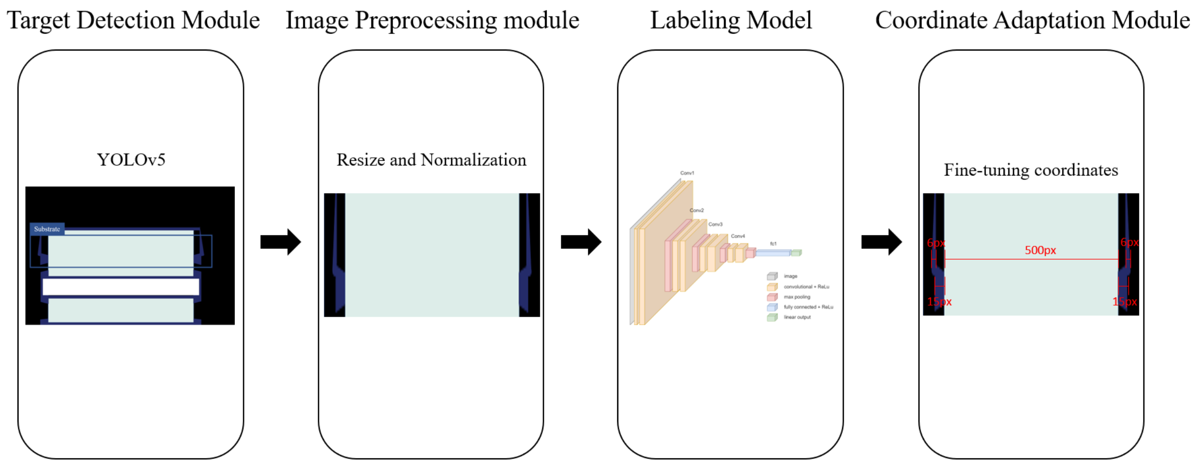


Fig. 2. DL-MM framework

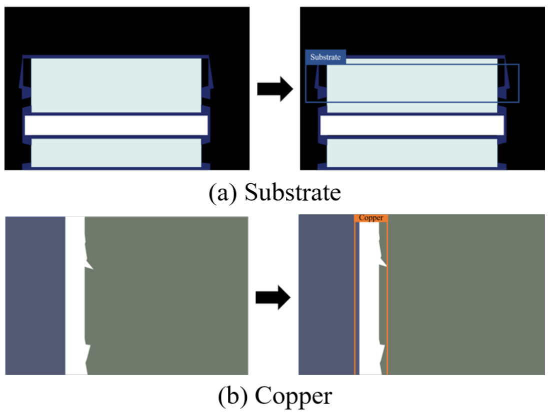


Fig. 3. Target detection module.

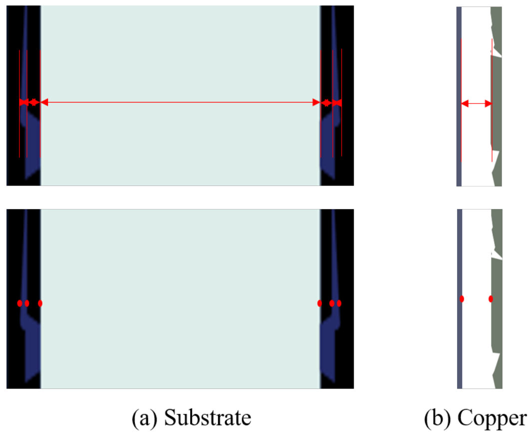


Fig. 5. Distance and coordinates.

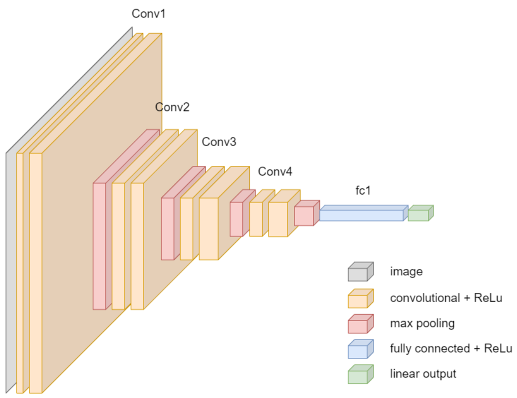


Fig. 4. The framework of labeling model.

## D. Coordinate Adaptation Module

In the coordinate adaptation module, to visualize the length predicted by the model, we convert the coordinates predicted by the labeling model into line segments and print the distance of the line segments on the image to observe easily. When we only want to know the distance of x, we average the y of the set of coordinates, update its coordinate value, draw a line segment with the two coordinates as endpoints, and print the length of the line segment next to the line segment for convenience Observed. As shown in Fig 6, we use substrate as an example.

# IV. Experiments

The distances and coordinates that need to be calculated are illustrated in Fig 5. The red line is the distance that needs to be known, and the red dot is the position that needs to be predicted. In our experiment, we first use LabelImg [16] to annotate the PCB slices that will be used to train the model. We compared the performance of using the image processed by our target detection module as the input to the model versus using the original image as the input. Since we aim to calculate distances, we have chosen the root-mean-square error (RMSE) as our evaluation metric.

In the experiments, there are two datasets: the substrate and the copper. The substrate dataset contains 70 images, while the copper dataset contains 140 imagess. For both datasets, we will use 80% of the dataset for training and 20% for testing. We use PyTorch to build our models. The optimizer is Adam. The learning rate is set to 0.0001. The mean square error is the loss function.

## A. Evaluation Metrics

After marking the model and calculating the width, we use the RMSE to assess the quality of the model by calculating

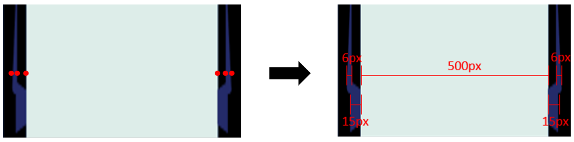


Fig. 6. Coordinate adaptation module.

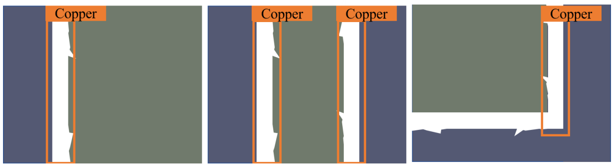


Fig. 7. Different quantities of features in Copper.

the average distance between the predicted and actual values. The RMSE is a metric used to evaluate the accuracy of regression models. The formula is as follows, where $y_i$ represents the actual distance, $y_i^p$ represents the predicted distance.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^p)^2}$$

### B. Target Detection

We designed the target detection module, which uses Yolov5 to extract the feature areas on the image in advance. This module obtains the ROI image and uses it as the labeling model's input to prevent unnecessary noise on the image. Moreover, it can also assist the labeling model in feature extraction.

Copper dataset may contain multiple features in a single image, as shown in Fig. 7. However, the labeling model can only predict one feature at a time. Therefore, ROI images must be obtained using the target detection module before performing predictions with the labeling model. Directly using the original copper image as input for the model is impossible.

### C. Result

The substrate dataset uses the original image input RMSE of 3.2, while the ROI image has an RMSE of 2.1, and copper uses an ROI image with an RMSE of 5.2. We can see that using ROI images has a much lower error rate than directly using the original images as input. Therefore, it is necessary to obtain ROI images in advance in the first step of the architecture.

## V. Conclusion

In this paper, we present a Deep Learning-based Microsection Measurement Framework. To address the challenge of having limited data and image noise, we developed a target detection module to enhance the labeling model's ability to capture relevant image features and minimize errors. As a result, the RMSE of the substrate dataset is less than 3, and the RMSE of the copper dataset is less than 6.

Furthermore, we have packaged the system into an executable form, allowing users to predict the element width without requiring a Python environment. The operation is straightforward and user-friendly.

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