IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 25, Issue 1, Ser. I (Jan. – Feb. 2023), PP 56-64
www.iosrjournals.org

Faulty Solder Detector System on Printed Circuit Board

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Abstract: *This paper presents a system for detecting faulty solder joints on printed circuit boards created by Automatic Welding Robot. The system consists of the Raspberry Pi 4 Model B, Raspberry Pi High-Quality Camera, Raspberry Pi 16mm Telephoto lens, and Touch screen 13.3" LCD V2 (H). Firstly, use the camera to take pictures of the printed circuit boards made from the automatic soldering robot. Next, use the labelImg tool to label the defective and missing solder joints. Use these images of solder joints to train and test the Yolov6 network to detect faulty and missing solder joints by the Google colab. Finally, the trained Yolov6 network will be deployed on Raspberry Pi 4 model B to detect the image of defective and missing solder joints from the printed circuit board image taken from the Raspberry Pi camera.The experimental results show that the proposed system can recognize defective and missing solder joints with over 98% accuracy and 100% recall.*
Keywords: *Yolov6, training, testing, solder joints, detect, defect, missing.*

Date of Submission: 25-01-2023 Date of Acceptance: 08-02-2023

I. Introduction

With the improvement of electronic circuit manufacturing methods, the production speed of electronic products is increasing rapidly. At the same time, in the process of assembling printed circuit boards (PCB), due to the reduction of component size and increased component density, the risk of errors is increasing (Qianru Zhang and colleagues, 2022). Therefore, an efficient and accurate quality control system is essential. Structural defects are one of the main types of defects in Printed Circuit Board Assembly (PCBA), including solder defects and short circuits. With the help of automatic detection method has reduced manual workload and minimized errors caused by subjective judgment and tester fatigue. Automated image-based inspection methods such as optical imaging and thermal imaging are commonly used in production lines for quality control. In (C. Zhang and H. Liu, 2011) authors used image processing techniques to pre-process the images of solder joint, then applies extreme learning machine (ELM) to recognize those defected solder joints. Experimental results show that the approaches can get a recognition rate of over 96%. The authors in (WU Fu-pei, ZHANG Xian-min, 2011) proposed a pseudo solder joint inspection method for lead-free solder joints in a Printed Circuit Board(PCB) based on analysing the solder joint image acquired by a 3-color LED structure illuminator and a colour 3-CCD camera. Three steps they used to detect the pseudo solder joints. Pseudo solder joints were inspected firstly by the centre of gravity method after positioning the solder joints and its components. Then, the regions of solder joints and components were figured out based on their edge, and the area method was used to inspect pseudo-solder joints. Finally, the missed pseudo solder joints were inspected by the proposed color grad method. The experiment results show that the proposed method composed of the center of gravity method, area method, andcolor grad method can inspect the pseudo solders effectively, and the inspection accuracy can reach 99.2%.Scientific literature (Kuk Won Ko et al. 2000) has been useda neural network with a fuzzy rule-based classification method. Their proposal consists of two parts: the first part used an unsupervised neural network and the second part is based on fuzzy set theory. The key idea of their solution is a fuzzy rule table reflecting the knowledge of criteria of a human inspector. The performance of the proposed approach was tested on numerous samples of printed circuit boards in commercially available computers, and then compared with that of a human inspector. Experimental results reveal that the proposed method is superior to the neural network classification method alone, in terms of its accuracy of classification. The authors (Horng-Hai Loh, Ming-Sing Lu, 1999) proposed a computer vision system for solder joint classification. Their system uses a novel structured-lighting inspection technology to overcome some difficulties that traditional computer vision systems often experience. They developed a slant map surface shape estimation technique for the solder joint. From this technique, a solder joint can be determined to be a good (concave), bad (convex), bridged solder joint or solder joint with surplus solder, or lacking solder

Recently, Yolo network has been used widely for detecting objects with high performance (H. Jonathan, 2018, Chuyi Li et al. 2022). Therefore, the authors propose Yolo network to recognize bad solder joints.

In this paper, the authorspropose an embedded system for recognizing defective solder joints. Firstly, they useRaspberry Pi High-Quality Camera to capture images from PCB that are produced by an automatic welding robot. Next, the proposed method usedthe labelImg tool for labeling bad solder joints. After that, these object images were used for training and testing the yolov6 tiny model using Google colab. Finally, deploy the trained yolov6 tiny model on the Raspberry Pi 4 model B for recognizing bad and missing solder joints of the PCB.

The paper is structured as follows, the first section is an introduction, and the second section presents the system that will be applied in the study, including the hardware and software for detecting bad and missing solder joints. The next section is the experiment results and the final section is the conclusion.

II. Proposed system

2.1. Hardware components

The proposed system hardware consists of theRaspberry Pi 4 Model B, the Raspberry Pi High-Quality Camerawith lens, and a touch screen. Raspberry Pi 4 Model B was released in June 2019 with many very significant upgrades that increase the performance of this mini-computer up to 3 times compared to the previous version. Figure 1 presents this embedded computer.

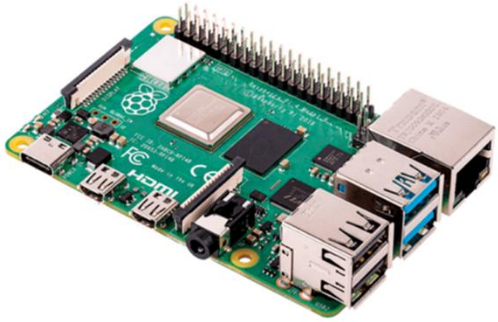

Figure 1. Raspberry Pi 4 Model B.

Raspberry Pi High Quality Camera is the newest Raspberry Pi camera accessory. It offers higher resolution and sensitivity (approximately 50% larger area per pixel for improved low-light performance) than the existing V2 Camera Module. Using Sony IMX477 sensor, FFC cable to connect to Raspberry Pi, black aluminum lens mount, hole to attach to a tripod, and C/CS focus ring. This is the first official high-quality camera module for Raspberry Pi.

The Raspberry Pi High-Quality Camera Module comes with a standard 15-pin FFC cable (15cm long) to connect to the Raspberry Pi board. This high-quality camera module is designed to work with lenses that use the C and CS mounts. Other types of lenses with adapters can also be used. A high-quality camera module requires a lens to work.

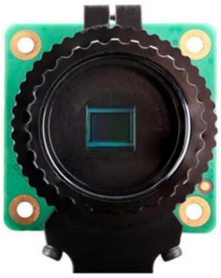

Figure2. *Raspberry Pi High Quality Camera module*.

Figure3. *Raspberry Pi 16mm Telephoto lens.*

13.3″ LCD V2(H) touch screen, with protective plastic cover and tempered glass, up to 1920×1080 resolution, HDMI interface, IPS panel, support various devices and systems.

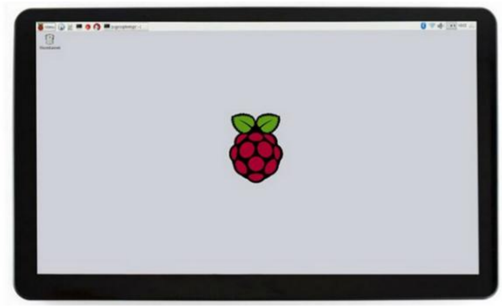

Figure 4. *LCD V2(H) touch screen .*

2.2. Connection hardware components

Connecting the touch screen to the Raspberry Pi 4 B is done as shown in Figure 5. Figure 6 depicted connection camera module to Raspberry Pi 4 B.

Figure 5.*Connecting touch screen to Raspberry Pi 4B.*

Figure 6. *Connecting camera module to Raspberry Pi 4B.*

2.3. Configure Raspberry to connect touch screen and camera module

In order for the Raspberry Pi 4B to display data on the touch screen, it is necessary to edit the config.txt configuration file of the Linux operating system. Add the following code at the end of this configuration file.

```
hdmi_group=2
hdmi_mode=82
hdmi_cvt 1920 1080 60 6 0 0 0
```

In order for the Raspberry Pi 4B to use the camera module, we need to go through the following steps:
Step 1: Start the Raspberry Pi;
Step 2: Open the Raspberry Pi configuration tool from the main menu;

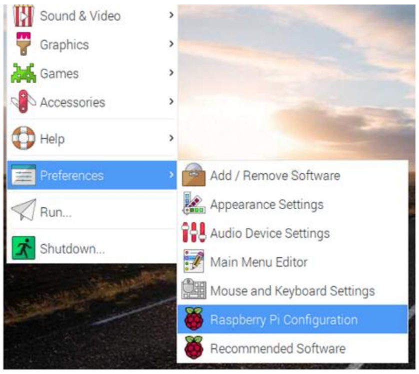

Figure 7. *Configuration windows.*

Step 3: Select the interface tab on the Raspberry Pi configuration window and select enable for the camera as shown in Figure 8;

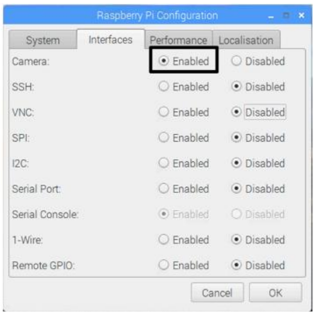

Figure 8.*Enable the camera on the Raspberry Pi tab.*

Step 4: Restart the Raspberry Pi.

2.4. Software

Algorithm flowchart of the solder fault detection system on the printed circuit board as shown in Figure 9. First, the image of the printed circuit is taken with a high-quality camera. Next, the bad solder joints from the printed circuit board image will be labeled with the LabelImg tool. Images and labeled objects will split into training and testing datasets for the yolov6 tiny model. Finally, the yolov6 tinymodel, after being trained and tested for accuracy, will be used to detect faulty solder joints on the printed circuit board provided by a high-quality camera connected to the Raspberry Pi 4 Model B.

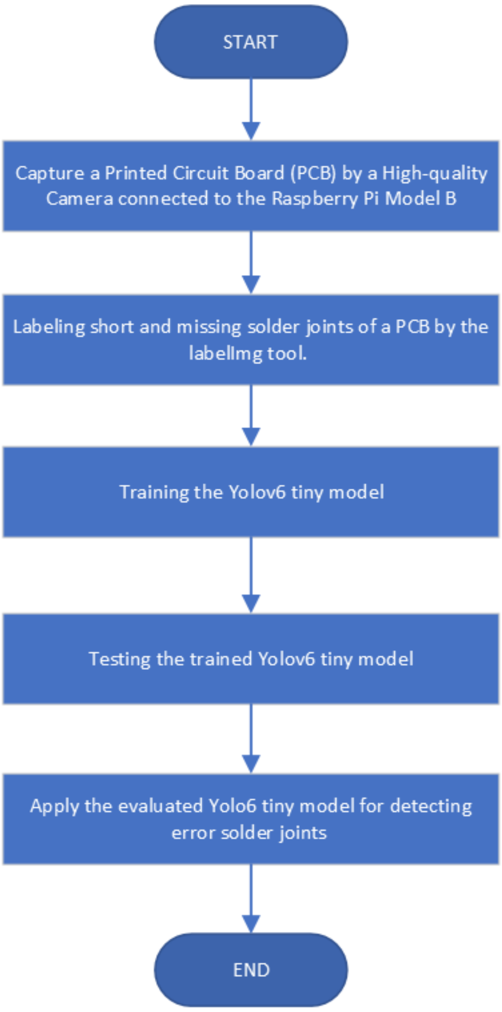

Figure 9.*Algorithm of the bad solder joints recognition system.*

2.5. Introduction to the YOLO

YOLO (You Only Look Once) solves the recognition problem as a regression problem. Instead of searching for regions of interest (selective search) like RCNN, YOLO generates bounding boxes for objects with their labels across the entire image in a single run of the algorithm. That's why it can be used for real-time object detection.

YOLO divides the input image into an $S \times S$ grid. Each grid cell predicts only one object. Example: yellow grid cell Figure 10: YOLO divides the image into grid cells below trying to predict the object “person” whose center (blue dot) lies inside the grid cell.

Figure 10. *YOLO divides images into grid cells.*

Each grid cell will be responsible for predicting a certain number of bounding boxes as shown in Figure 11: Two bounding boxes of a grid cell, the yellow grid cell has two frame predictions to determine the location of the person.

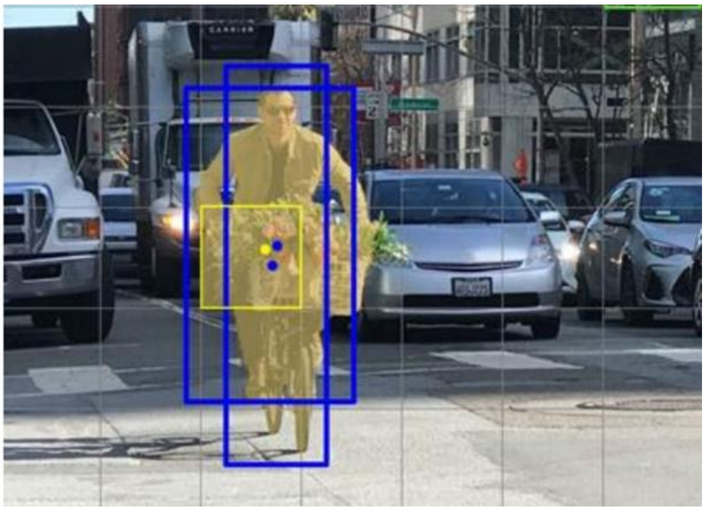

Figure 11. *Two bounding boxes of a grid cell.*

For positions on the grid, the position closest to the centre of one of the ground truth bounding boxes is considered a positive position, and the remaining positions will be considered negative positions.

Each grid cell will predict the *B* bounding box and each box will have a confidence score, and will also predict C the probability of that cell's class for the degree of compatibility with the feature. In the first version, YOLO used 7x7 grid cells (*SxS*), 2 bounding boxes (*B*), and 20 classifiers (*C*). Each bounding box contains 5 elements: (*bx, by, bw, bh*) and the box's confidence score. The confidence score reflects the likelihood that the box contains an object or not and the accuracy of the frame. First, the width and height of the bounding box w and h will be normalized to the width and height of the image.x and y will also be calculated according to the coordinates for the respective cell. So *bx, by, bw* and *bh* are all between 0 and 1 (H. Jonathan, 2018).

Each grid cell has 20 probability scores of the conditional classes. The conditional class probability is the probability that the detected object belongs to a particular class. So, YOLO's prediction will have the following dimensions: ($S, S, B \times 5 + C$) = (7, 7, 2 × 5 + 20) = (7, 7, 30), Figure 12 illustrates the final output of the YOLO architecture.

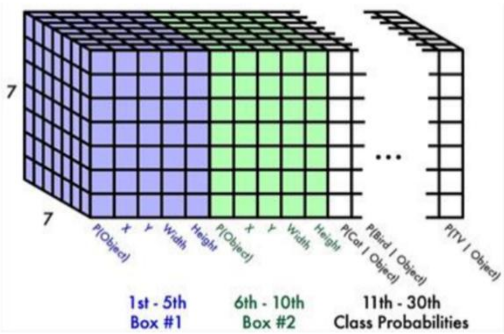

Figure 12. *Last output of the YOLO model.*

The main idea of YOLO is to build a CNN network to predict a tensor of the final output size (7, 7, 30). It uses the CNN network to reduce the spatial size to 7×7 with 1024 output channels. YOLO then performs linear regression using two fully connected layers to generate 7×7×2 boundary box predictions. YOLO has 24 convolutional layers followed by 2 fully connected (*FC*) layers. Several 1×1 convolutional layers are used to reduce the depth of feature maps. For the final convolution layer, it outputs a tensor with shape (7, 7, 1024). To make the final prediction, YOLO keeps the boxes with the highest confidence scores (greater than the threshold) to make the final prediction. The faster but less precise version of YOLO, called Fast YOLO, uses only 9 convolutional layers with a smaller feature map.

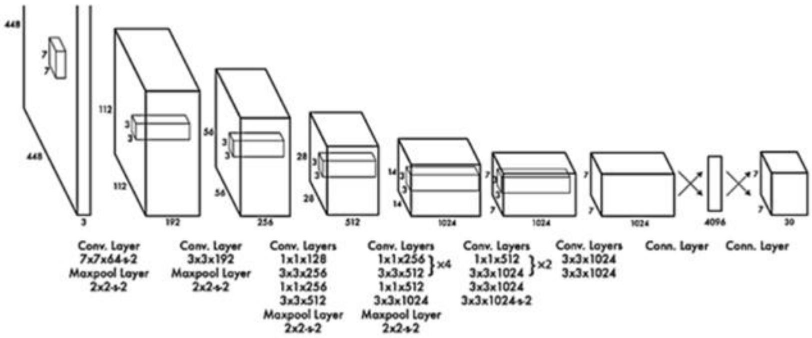

Figure 13. *Architecture of the YOLOnetwork.*

The class confidence score for each bounding box is calculated as follows:
- Confidence score of object bounding box: *Pr(object)*IoU*;
- Conditional probability of class: *Pr(classi/object)*IoU*;
- Class confidence score: *Pr(classi/object)*Pr(object)*IoU*.

where:
- *Pr(object)* is the probability that the bounding box containing the object can belong to any class, also known as objectness.
- *IoU* (Intersection over Union) is the ratio of the intersection to the union between the prediction frame and the correct frame, also known as the ground truth.
- $Pr(class_i/object)$ is the probability that the object belongs to the i^{th} class provided the frame contains the object.
- $Pr(class_i)$ is the probability that the object belongs to class *i*.

The class confidence score for each prediction bounding box contains both probabilistic information that the class type is inside the box and information about the accuracy and fit between the bounding box and the object.

III. Experimental Results

To test the performance of the proposed system, we collected 120 solder joints that are shorted and 150 solder joints that are missing. We divide the dataset into two subsets. The first subset is the training set containing 80% and the second subset is the test set containing 20%. In this study, we use transfer learning, so we download the trained YOLOv6 network model with real-world object data from Git Hub. This model is saved in the YOLOv6/weights folder.Because of the lack of samples for the training model so we use Google colab to train the pre-trained model 1000 epochs with the training data set. After that, we test the trained model by the test set. Table 1 summarizes the test results in accuracy and recallsmeasures.

Table 1. The test results

Error type	Accuracy (%)	Recall (%)
Short Solder joint	99.2	100
Missing solder joint	98.6	100

Figures 14, and 15 illustrate capable of the model to recognize short and missing solder joints. In the last figure, the pink boxes are missing solder joints and the red boxes are short solder joints.

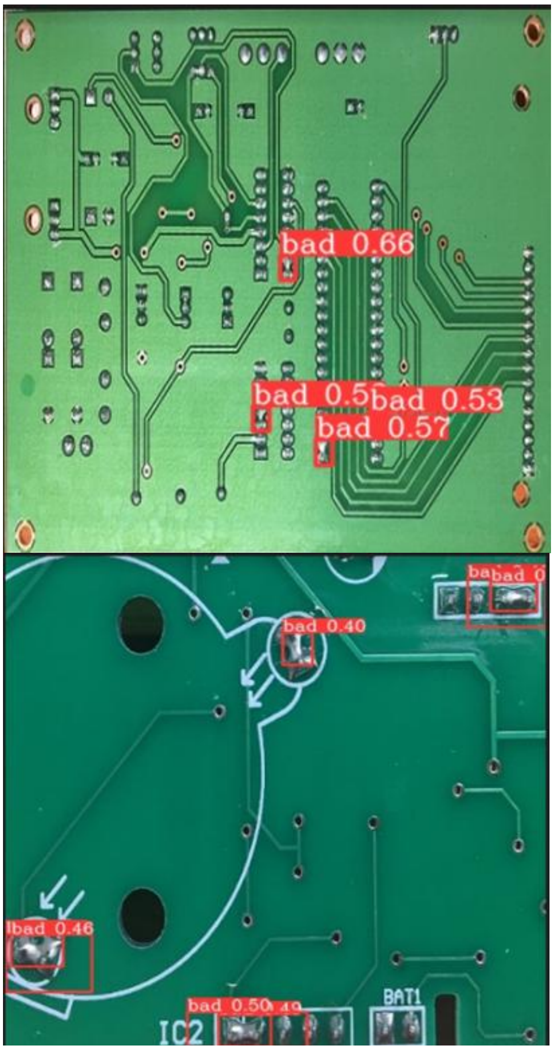

Figure 14. *Detecting short solder joints.*

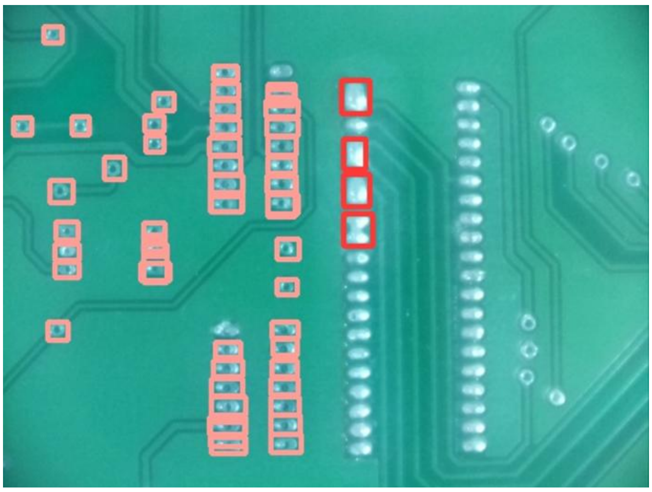

Figure 15. *Detecting short solder and missing joints.*

Figure 16. *The proposed real-time detecting system*

IV. Conclusions

In this paper, the authors present the system for recognizing short and missing solder joints. The system hardware consists of a high-quality camera, touchscreen, and Raspberry Pi 4 Model B. The software includes a module to capture images from a high-quality camera using an open CV library written in Python language, Yolov6 tiny model is trained by the Google colab with a training dataset. After that, the trained model is deployed in Raspberry Pi 4 Model B for real-time recognition of bad solder joints. The system can detect short and missing solder joints with an accuracy of over 98% and 100% recall. In the future, we will study to expand this system for detecting other types of bad solder joints such as pour-quality solder joints.

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Dung Vuong Quoc, et. al. "Faulty Solder Detector System on Printed Circuit Board." *IOSR Journal of Computer Engineering (IOSR-JCE)*, 25(1), 2023, pp. 56-64.