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Application on PCB Defect Detection System using multi-Axis Arm Integrated with Optics and Deep Learning Technology

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Abstract

As technology became more advanced, a lot of products have included electric circuits in order to increase their capabilities. The demand for circuit boards rises naturally alongside with the demand for these products said above. Many manufacturers have started to incorporate automation systems into their production lines, which has increased productivity in various industries and helped them to cope with manpower shortages. As circuit boards become an important aspect in almost everything, the demand for higher yields and production quality increases, and line automation, including artificial intelligence such as robotic arms and machine learning, becomes more common in the manufacturing industry. In the circuit board manufacturing industry, more and more new products are being introduced and the demand for circuit boards is increasing, so better quality control and production efficiency are required. The industry has been using automatic optical inspection machines for about 20 years to identify defects in circuit boards, but currently relies on manual repair processes, which are inefficient and prone to errors. The system can be integrated with the robot arm, using artificial intelligence

and computer vision to classify images and control the arm to perform repair to improve the efficiency of the board manufacturing process and reduce the cost of repairing boards, which can maximize the production line and increase the profitability of the company.

Keywords: *Printed Circuit Board, Image Classification, Automated Optical Inspection, Deep Learning*

1. Introduction

Automated industry refers to the automation of machines, robotics, and computer systems doing tasks previously done by humans. Reasons like shortage of skilled labor and demands for higher productivity and quality causes an industrial sector to adopt automation [1]. Automation can help improve efficiency, reduce costs, and increase productivity in various industries, including the manufacturing industry.

Robotic arms are the most common type of automation used in the industry, having the advantages of being more accurate and cost-effective. The most common application being material handling and pick-and-place jobs, in which changes human role from doing the labor work to monitoring those arms. Reducing the risk of work events and improving the efficiency of the manufacturing process.

Artificial intelligence (AI) also plays a huge role in the whole manufacturing industry. AI is the ability of machines and computer systems to perform tasks that normally require human intelligence, such as learning, problem-solving, and decision-making. AI is an interdisciplinary science based on disciplines such as computer science, biology, psychology, linguistics, mathematics, and engineering, with multiple approaches. There are several ways to achieve AI, but machine learning is the most common way to go, and deep learning is a special type of machine learning. Machine learning enables systems and machines to learn automatically and improve from self-experience without being explicitly programmed [2]. Machine learning provide the ability of predictive maintenance, process optimization, task scheduling, quality improvement, supply chain, and sustainability etc. in the industry [3].

In recent years, due to the rapid growth of electronic products, the quality and productivity requirements of electronics manufacturing have become strict and complicated. This in turn increase the demand for printed circuit boards (PCBs). In order to compete with rocketing demand, this industry innovated the automation system of PCB manufacturing. Nevertheless, the system may create some defects while manufacturing the PCBs. Defects like open solder joints and solder bridging may happen to PCBs either using surface mount devices and through-hole although both use different soldering methods. Temperature control is an important key to manufacturing a PCB without defects. Although current manufacturing systems have already included sensors to control the temperature of solder, this doesn't completely solve said defects. Thus, the role of AOI (automated optical inspection) machine came to place. The AOI machine inspects every solder joint looking for the presence of any defects. Then it informs the user of the defect to be corrected. Currently, the correction part is still using manual labor, which may again create skill-related issues. Our system integrates the automated optical inspection system and robotic arm, improving the efficiency of the current PCB manufacturing industry.

2. Principle and Method

Utilizing computer vision library capturing the image and processing them for the trained AI model to execute image classification. Then the classification result which contains coordinates is then sent to the robotic arm and moves to the coordinates accordingly. The arm, installed with soldering iron and solder will do the correction on the defect solder joint. This process in which conventional PCB manufacturers usually uses human labor to do the correction on the defect solder joint, a method not very efficient that may cause human error. The core of a conventional AOI machine contains a camera or an optical sensor as the capturing device and a lighting system which allow better solder inspection. The system uses several LED rings surrounding the target object and capturing device in the middle of those rings. The machine contains software which is designed for identifying certain defects on components in PCB boards.

2.1. Image Processing

The use of a digital computer to process digital images through an algorithm which involves applying mathematical operations to the pixel values of an image in order to enhance, transform, or analyze the image[4]. Algorithms used such as filtering, segmentation, transformation, feature extraction, and image restoration.

Thresholding, a method used in this system replaces each pixel in an image with a black pixel if the image intensity is less than a fixed value called the threshold T, or a white pixel if the pixel intensity is greater than that threshold. Another method used, warp perspective, deforms the pixel grid and map this deformed grid to the destination image.

2.2. Image Classification

Azure Service is a cloud computing service which is a cost-effective alternative for locally installed computing clusters, providing computing resources and data storages that are virtually without limit, not interrupted by other users' applications or system maintenance, and charged by usage only [6]. The service includes machine learning which is used in Azure's own computer vision that will be used in our classification model. The model will be exported into a Tensorflow model, a deep learning framework that offers better usability and higher performance.

2.3. Robotic Arm

Industrial robotic arm commonly classified as cartesian, cylindrical, spherical, SCARA, articulated, and delta robots. Cartesian robots have the advantage of being simple and relatively simple, it has the speed and agility limit due to its design using three linear axes that move the arm in a straight line. Cylindrical, spherical, SCARA robots have advantages of their agility, however the design using only 3 axis lacks the flexibility we need. Thus, we chose the articulated robot arm for our system. The robotic arm is then controlled via Epson RC in which connects the arm PC-based core via wired connection. Epson's program API can also be executed in LabVIEW.

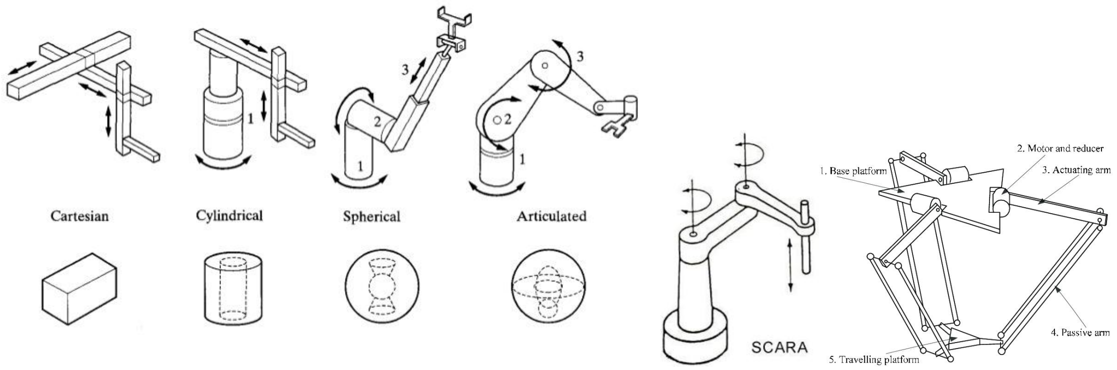

Figure 1. Types of Robotic Arms [7]

3. Hardware and Software System

The structure of the system utilizes PC-based core with integrated with camera module and a robotic arm which is displayed as a diagram in figure 2. When the object arrives on the detection area, the camera captures the image and start executing the reshaping process of said image. With the image reshaped, the system core may divide each solder joints and execute the classification process with a machine trained model, in which location of defect joints are fed to the robotic arm, being converted to a coordinate that the robot understands, directing to those coordinates.

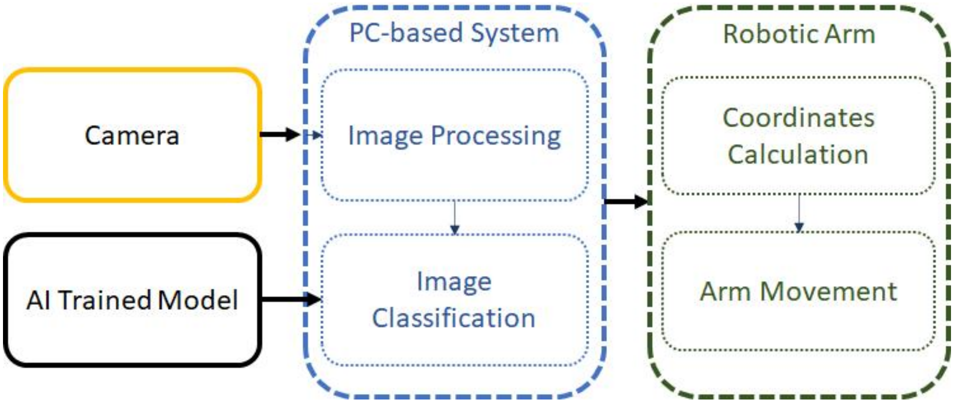

Figure 2. System Structure Diagram.

Based on figure 3 below, in the image processing operation, thresholding is applied to the captured image to get the pixel-array locations of the border. Then further calculations are made to create a matrix to be applied on the original pixel-array in order to warp the perspective of the object to a straight top view. Lastly, image is then sliced into each joint where it will be used for image classification. The image classification made use of Azure AI model which is trained and exported to a Tensorflow model file, increasing the efficiency by decreasing the execution time. The result is returned in the shape of a dictionary containing result as keys and position as values. Returned dictionary is then given to the robot arm to be converted to an XYZ coordinate, which the arm movement functions can read and directly move precisely based on it. The whole procedure is run in LabVIEW which contains the Python and Epson Robotic Arm API. This process unifies the system making it working on one core connecting different platforms instead of multiple platforms working indirectly.

Above AI model uses machine learning method which creates more flexibility in classifying objects, unlike pattern match and template match which may be limited to fixed defect shapes and problems detecting images that may seem rotated from taught sample. The reason to exporting an Azure AI model into a Tensorflow model is to remove the process of uploading classification image to Azure servers but still keeping the ease-of-use feature of Azure in mind for future data analysis i.e., what shape or model has more defect solder joint and other kind of trends.

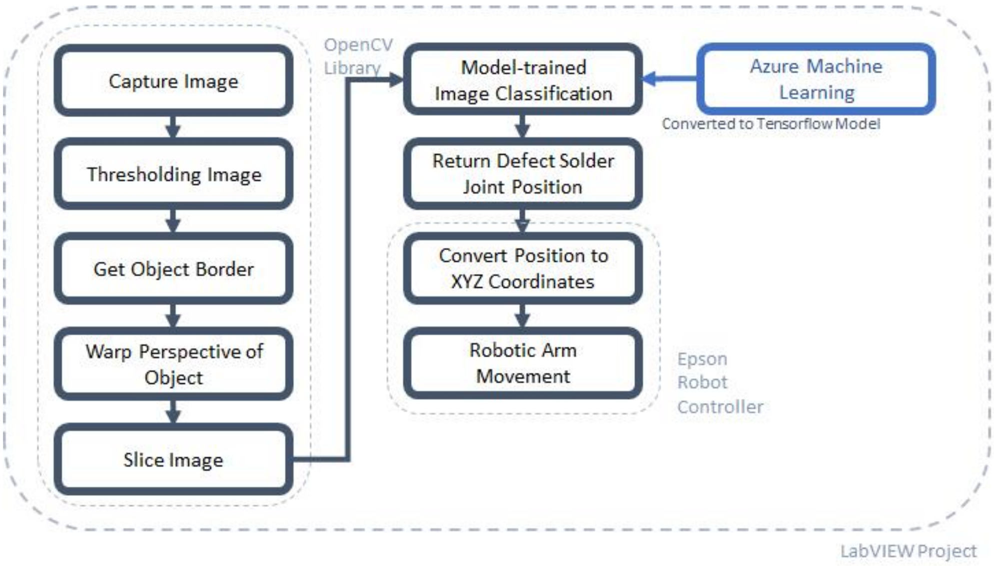

Figure 3. System Flowchart.

4. Results

With the system environment designed as Figure 4, the circuit board first will be moved by the conveyor belt to be under the camera module. In this position, the whole object may be captured by the camera's lens and with the assistance of the LED ring, the contrast between empty joint and joints with solder are enhanced. The captured image based on the system flowchart above have its background cut, acquiring a clean image of the object and then sliced for image classification (Figure. 5). Then the conveyor belt moves the circuit board into the predetermined position under the arm where the arm executes the correction step on the defect solder joints.

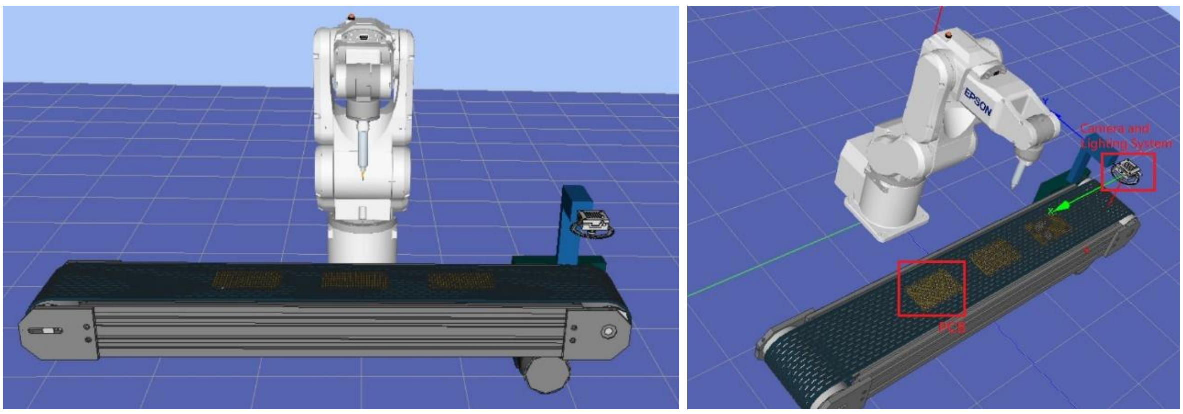

Figure 4. Epson RC's virtual environment simulating the correction step in the automation system.

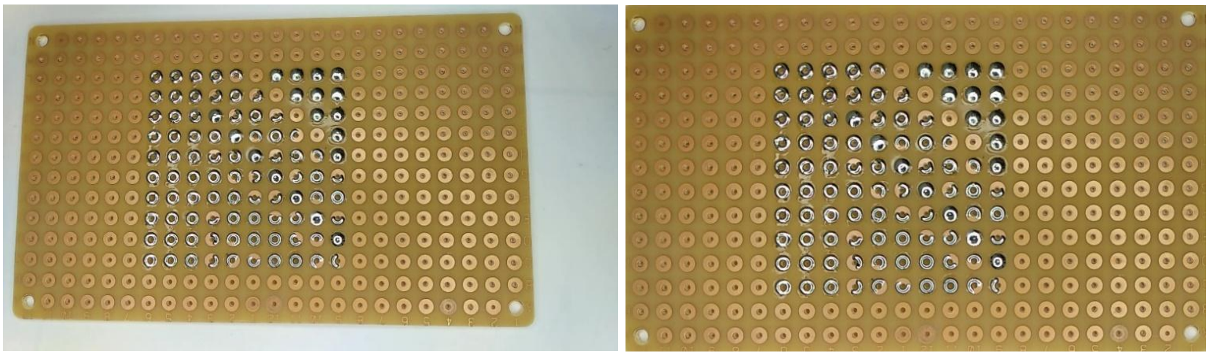

Figure 5. Captured image (left) with rewrapped perspective (right)

In the classification process, the sliced image is then compared to the color range of solder tin to determine the presence of solder tin in the joint, as in Figure. 6. If there is no solder detected, said part of sliced image will not be compared with the classification model, saving resources and shorten the processing time. The AI model itself will determine the quality of a joint whether it is good or containing a defect. In our case, the classification result is divided to 3 conditions, no defect found, joint and component not soldered together, and joint lacking solder. Each being framed with green, orange, and red rectangle respectively The AI model may be retrained for more detailed classification or in case of different joint shapes.

Figure 6. Sliced image with (right) and without (left) solder tin.

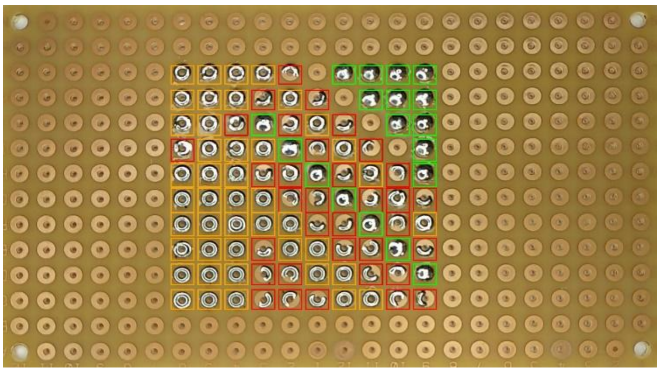

Figure 7. Classification result being framed with different colors.

In these testing process, we gave 250 solder joints with results shown below (Table 1). 97.2% of results returned were accurate, 2.4% of results were misclassified although still classified as defect joint, which can be tolerated. Only 1 sample did classify a defect joint as a correct one.

Table 1. Testing results of 250 solder joints.

	Amount returned	Percentage
Accurate Classification	243	97.2%
Misclassification (yellow classified as red)	6	2.4%
Defect joint as no defect joint	1	0.4%

5. Discussion

Every innovation has a space for improvement, either does our system. During the testing process, we trained the classification model twice, where the first version of the model had difficulties classifying object which are nearby the borders of the board. We then include more sample that was located away the center, the results using the second model after adding updated samples solved this problem.

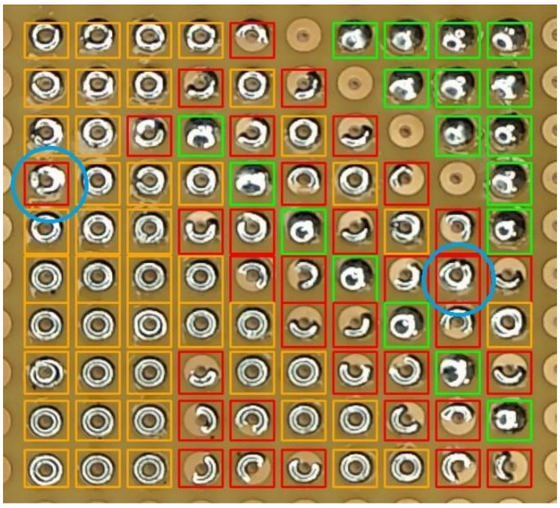

Figure 8. Misclassification is framed with blue circle; one in left, one in right.

Table 2. Testing results of 250 solder joints.

	Valid Classification	No defect / Green frame (%)	Not soldered together / Yellow Frame (%)	Lacks solder / Red Frame (%)
Left	Not soldered together	4.9%	66.3%	70%
Right	Not soldered together	5.7%	22.7%	32.2%

The results of the test using 250 objects showed that the model made 6 misclassifications. In order to better understand the reasons for these errors, we selected 2 of the misclassifications for further analysis. The results returned from the classification model, as shown in the table above (Table 2), indicate that the model had a relatively high level of confidence in its classification decisions. In both of the cases that we analyzed, the difference between the valid classification result and the result returned by the model was less than 15%. While any misclassification is a cause for concern, the relatively small margin of error in these cases suggests that the model may be able to be improved by correcting certain aspects of its performance. Solving this issue can be done refining the model in order to improve its accuracy and reduce the number of errors in the future. Last, we also noticed that the light emitted from the ring light is reflected on the soldered surface. While it is normal for solder to reflect light, more intense reflection might not fit the toleration of the classification model affecting its result. Thus, a change to the lighting system will be done in the future in order to decrease the clarity of the reflection on the soldered surface.

6. Conclusion

The adoption of automation and the use of robotic arms in the manufacturing industry has significantly increased production capabilities across various sectors. Many products that are manufactured today contain at least one or more printed circuit boards (PCBs), leading to an increase in demand for PCBs. In response to this demand, PCB manufacturers have also increased their production levels, which has led to a need for more labor to inspect and correct any issues that may arise during the manufacturing process. One way that manufacturers have been able to improve the accuracy of the inspection and correction process is through the use of image processing techniques, such as those implemented through OpenCV. By training machine learning models on these technique applied objects, manufacturers can classify images with a higher degree of reliability. The integration of these techniques with robotic arms enables the PCB manufacturing industry to move closer to a fully automated production line.

LabVIEW is a software platform that allows for the integration of these key techniques and can be installed on a PC-based system to assist with the PCB manufacturing process. By using LabVIEW and robotic arms, manufacturers can allocate labor that was previously used for correction tasks to other areas of the production line, increasing efficiency and reducing costs. In the future, it is likely that the data collected from the system application in the production line will be stored in a database and used for big data analysis. This data can be used to refine the accuracy of the classification model and improve the overall accuracy of the results. Additionally, the data collected can be used to identify trends in defects that occur during the manufacturing process. These trends may reveal which solder joint specifications or design layouts are more prone to defects, allowing manufacturers to improve their processes and reduce the defect rate, ultimately leading to fewer corrections being needed.

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