A Real-Time Automated Visual Inspection System for Printed Circuit Boards Missing Footprints Detection

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***Abstract*—Visual inspection systems (VIS) are vital for recognizing and assessing parts in mass-produced products at the fabricating lines. In the past, item review was carried out physically, which made finding imperfections repetitive, moderate, and prone to error. VIS may be a strategy to abbreviate preparing times, boost item quality, and increment fabricating competitiveness. For the reason of reviewing lost components on uncovered printed circuit sheets, a visual inspection framework is required. The assessment assignment has become more challenging to accomplish the specified quality due to the more compact and complex surface of structured electronic components. This study proposes a real-time visual inspection system to assess lost impressions on Printed Circuit Boards (PCB). This system is composed of hardware and software frameworks. The main contribution of this study is the proposed software framework. The software framework consists of components region analysis and missing detection using image processing, cross-correlation, and production rules. Experimental results show the viability and achievability of the proposed system for PCB missing component detection.**

Keywords—Automated visual inspection; Printed Circuit Boards (PCB); quality control; image processing

I. INTRODUCTION

Printed circuit boards (PCBs) are a pillar of the electronic manufacturing sector [1,10]. The process of PCB inspection is challenging to perform manually because the surface of electronic goods is increasingly compact and complicated. This makes it harder for electronic boards to achieve quality control on the final products. The AVIS is the answer to boosting productivity and avoiding the challenges of manual inspection and mostly used in smart manufacturing [2,11]. Although many studies have been done on PCBs inspection, the issue of missing footprints has received less attention. When a "Printed Circuit Board" is created and released onto the market, the consumer of the board needs footprints (component shapes) in order to locate the location of the electronic component on the board [3,7].

The methods of human-based inspection for finding flaws depend on the expertise of the inspectors utilizing conventional tools, which makes finding flaws tedious, sluggish, and prone to mistakes [12]. This study thus concentrated on PCB footprint verification utilizing machine vision in the production line. These footprints are categorized by the AVIS utilizing a rule-based classifier and a machine vision system based on print quality [1,8]. As the global marketplace demands more emphasis on quality, automated visual inspection of industrial items for quality control plays an increasingly important role in the manufacturing process [2,9]. Most of the time, people still do visual examinations for quality purposes. However, human-based inspection suffers from many challenges: low inspection speed and accuracy fluctuations.

This study presents an automatic visual inspection system for PCB missing component detection. This work is based on pure image processing algorithms which provide efficient and less computation cost techniques to represent and detect faulty PCB products. The categorization of fault types is done using a proposed production rule. Additionally, the finished footprints on the PCB are identified using Template matching.

In following section, related works are reviewed in Section II. The proposed method describes in Section III. Section IV presents the experimental result. Finally, the paper concludes in Section V.

II. RELATED WORKS

This section presents related works on automated visual inspection systems in the PCB quality control process.

Wu et al. [1] developed a method for automatic visual examination based on characteristics of solder connections on PCBs, such as their location, shape, and logical aspects. The suggested technique may be used to identify various PCB defects, including no solder, surplus solder, incorrect or missing components, and damaged components. The characteristics will be retrieved based on several locations and the geometry of the solder connections once the solder joints have been localized. From solder junctions, they obtain occupancy ratios for the area, color, center of gravity, and continuous pixels. The logical features are recovered by examining the tight relationships between form, location, and colour dispersing factors.

Matsushima et al. [2] proposed a neural network-based visual inspection solution for PCB solder connections. For the learning and inspection phases, input data characteristics are retrieved using principal component analysis (PCA). The camera angles and the light source determine the circumstances for capturing images. There are two phases in a neural network visual inspection system: learning and inspection. In the learning phase, the neural network system produces two outputs, the defect degree and the good degree of the sample, based on the inputs retrieved from a good or defective sample.

The neural network's input for the learning phase is the Principle Component Analysis (PCA) generated as a feature from the sample pictures.

After placing wet solder paste on a printed circuit board, Zhang et al. [3] created a real-time visual assessment method of the solder paste quality. In this approach, the extraction of the region of interest, which includes the solder paste and pad regions, begins with a segmentation procedure. The categorization of five kinds of solder pastes as Good, Excess, Insufficient, Horizontal displacement, and Vertical displacement is then performed using a neural network algorithm.

Brunetti et al. [4] proposed a solder connection flaw detection system using automatic optical inspection (AOI) for PCBs produced using the surface mounting method (SMT). The neural network technique solves this diagnostic as a pattern recognition issue. The pictures are obtained using horizontal, vertical, and correlation coefficients. Each region of interest is assessed using three different types of feature vectors: geometric features (G-feature), wavelet features (W-feature), and the combination of the two features (GW-feature). According to their experiment, the best recognition rate was attained using a Multi-Layer Perceptron (MLP) network and GW features.

Lin et al. [5] developed a method to inspect printed circuit boards more quickly and accurately. The inspection process consists of two steps. Only one image characteristic is abstracted from the picture in the first step, and it is utilized as a screening index to filter out most typical components quickly. The neural network is then used as a classifier along with picture indices such as the histogram index, correlation coefficient, high contrast index, and regional index.

III. PROPOSED SYSTEM

The architecture of the systems that are suggested in our study is shown.

A. Hardware Framework

Fig. 1 shows the hardware framework's organizational structure. It incorporates the web camera used for picture acquisition, a conveyor belt, a light source, and a laptop system with image processing software.

The AVIS framework aims to classify the footprints into complete and incomplete shapes related to LED, Resistor, IC, Capacitor, and Transistor footprints. The specific algorithms are detailed in the paragraphs that follow. The camera, light source, and conveyor belt, which make up the three main parts of our real-time imaging system, are calibrated in simulated settings. Fig. 2 depicts the hardware for the suggested AVIS model and is explained in the following subsections.

As shown in Fig. 3, a webcam is used to capture images. The PCBs are moved along the conveyor belt at the chosen pace and in the desired direction, from left to right, simulating a true industrial setting. The stand is used to secure the camera to the conveyor belt and allows for up-and-down movement of the webcam. Additionally, the camera is fixed to a pedestal and is positioned in the middle of the conveyor belt. The webcam is best positioned in the center to catch the PCBs as they go along the conveyor belt. The actual capture of the picture, segmentation, and classification are done on the computer.

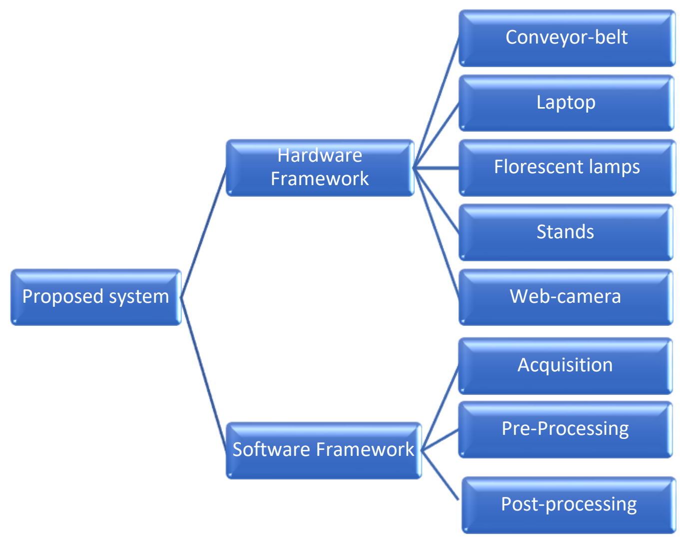

Fig. 1. The proposed system.

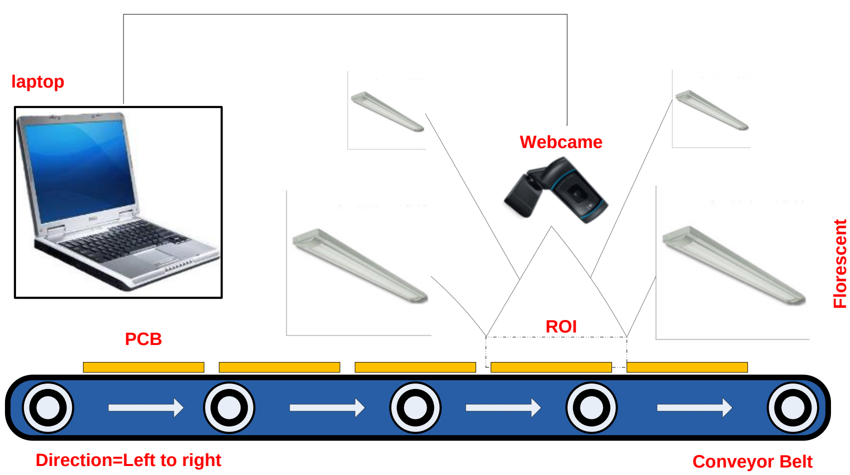

Fig. 2. The proposed hardware framework.

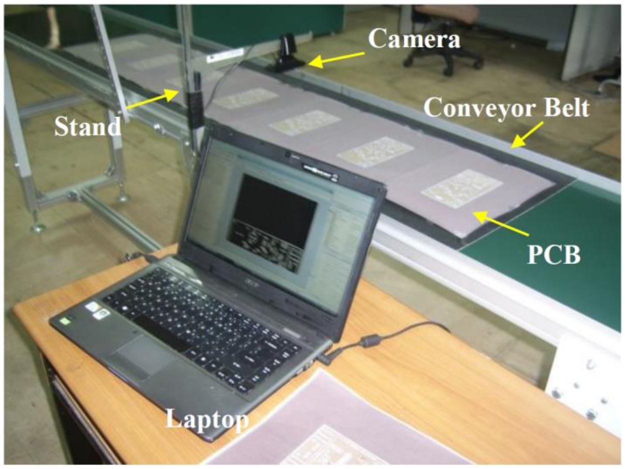

Fig. 3. AVIS model hardware in the real environment.

B. *Software Framework*

The software diagram depicted in Fig. 4 represents the proposed AVIS software framework. The processes for object detection and picture processing are included. Feature extraction, board location, segmentation of footprints, and image collection are the first five processes. The images are then categorized in terms of their geometrical features using a production rules method.

1) Image acquisition: The acquisition systems feature a mechanical positioning tool to move the camera or the product being tested to a fixed position and acquire the picture. The program displays the outcome and waits for the following acceptable image. The program recorded RGB frame-by-frame photos of PCBs traveling on the conveyor belt at a set conveyor belt speed.

2) Image segmentation: The pre-processing stage consists of two steps of image segmentation. The first image segmentation step is to extract the board under inspection from the acquired images, while in the second step, the image of the footprint is obtained from the board image. We have explained the two steps in detail.

a) Board localization: The work carried out in this stage of pre-processing is the extraction of the board from the obtained image. In any instance, a procedure to lessen or eliminate discrepancies between the obtained picture and the ROI must be included in the pre-processing [4]. In this case, we used a connected component to locate the board from the collected picture. In this project, the connected-component labeling procedure will use an 8-connectivity pixel since it is assumed that forms are frequently far from one another. As a consequence, calculation complexity can be avoided [6]. The largest component among those found to be connected is then extracted from the group based on size, and in this case, the largest component is the whole board, as shown in the obtained image. The steps of board localization are depicted in Fig 5.

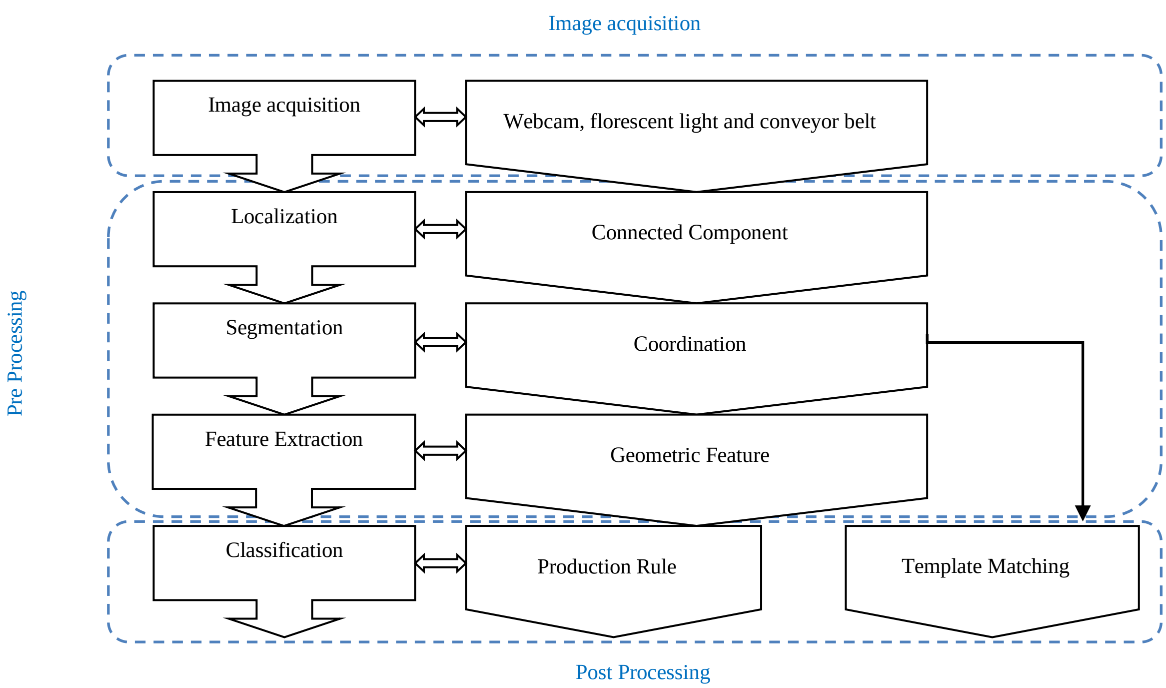

Fig. 4. The software framework.

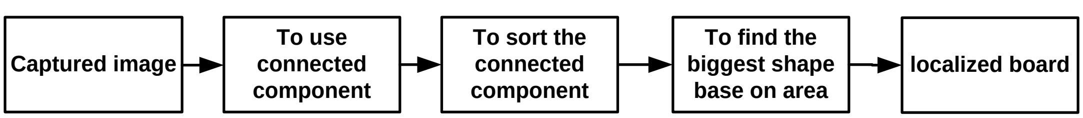

Fig. 5. The steps of board localization.

b) Footprint segmentation: In this step, each region of footprints is cropped the based on its coordination in terms of PCB's size. In this instance, we cropped the bounding box using four parameters: X_{min}, Y_{min} (Coordination), width, and height. First, the segmented image's energy will be assessed. If the segmented image's energy is greater than 15 pixels, the following stage will be to assess the printing quality. The entire footprint would be missing if the energy level were below 15.

3) Feature extraction: The feature extraction stage of image processing is crucial. The application and success of every classification method in the next phase depend on choosing the most appropriate characteristics. The subsequent phase of our procedure is feature extraction. From linked components on the footprint that were acquired by segmentation, a geometric feature [4] has been retrieved in this part. This method investigates two types of significant geometric properties, Area and Perimeter, for each item in the image based on the previously given information.

4) Classification: Image classification is the last phase of the proposed software framework. When the features are retrieved, a classification may be made using a set of known features in this step. In this study, the area and perimeter characteristics are the geometrical features chosen for the classifying footprint. Production guidelines are used to categorize the footprints into four groups in this step: 25%, 50%, 75%, and 100% for each type of footprint. Different types of footprints on a PCB are dealt with by the models for detection and categorization (Variable resistor, IC, Capacitor, LED, Transistor). Tables I, II, III, IV, and V show the types of footprints.

5) Production rules : In this work, the classifier is rules-based. An effective and simple system is founded on rules. The IF-Then structure states that IF can develop a set of rules that can achieve a high classification rate for these specified classes of footprint and can then claim that rule-based systems are feasible. Calculated rule-based output takes the form of rules based on the area and perimeter of forms. The variable resistor takes just Area. Each object can get one of the values: (25%, 50%, 75%, and 100%). Table VI shows the features and values in each segmented image. Fig. 6 shows the inference engine of the production rule for four classes of footprints.

The V1 to V6 represent the perimeter of shapes in a segmented image. The V7, V8, V9, and V10 represent the Area of shape in a segmented image. The values of perimeter and area are different for each type of footprint.

TABLE I. THE FOUR CLASSES OF THE CAPACITOR

Type of footprint	Quality of the printing	Percentage	Accept or reject
Capacitor		25%	Reject
		50%	Reject
		75%	Reject
		100%	Accept

TABLE II. THE FOUR CLASSES OF THE VARIABLE RESISTOR

Type of footprint	Quality of the printing	percentage	Accept or reject
Variable Resistor		25%	Reject
		50%	Reject
		75%	Reject
		100%	Accept

TABLE III. THE FOUR CLASSES OF THE IC

Type of footprint	Quality of the printing	Percentage	Accept or Reject
IC		25%	Reject
		50%	Reject
		75%	Reject
		100%	Accept

TABLE IV. THE FOUR CLASSES OF THE TRANSISTOR

Type of footprint	Quality of the printing	Percentage	Status
Transistor		25%	Reject
		50%	Reject
		75%	Reject
		100%	Accept

TABLE V. THE FOUR CLASSES OF THE LED

Type of footprint	Quality of the printing	percentage	Accept or reject
LED		25%	Reject
		50%	Reject
		75%	Reject
		100%	Accept

TABLE VI. THE FEATURES IN CLASSES OF FOOTPRINTS IN SEGMENTED IMAGE

Feature	value	Feature	value
	25%		100%
Perimeter	50%	Area	
	75%		Less100%

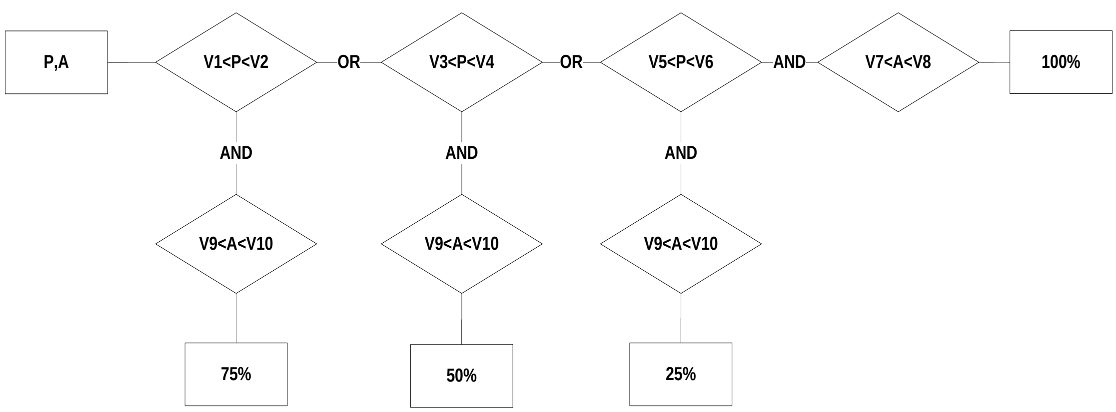

Fig. 6. The inference engine of production rule.

IV. EXPERIMENTAL RESULT

This section discusses and presents the results of each module using a standard for evaluating computer software. Each module's step's performance is calculated. These procedures comprise capturing the picture, board localization, segmentation, and classification of the footprint. When the PCBs are in the webcam's field of view, the program instructs the webcam to take a picture by using a region of interest (ROI). Using three criteria, the program evaluates the ROI for each frame. The image's top, bottom, and middle thirds are our focus areas. Three regions' total quantity of white pixels will be determined. The PCB picture was taken in ROI by the technique chapter's instructions. Using a set threshold in the region of interest, the collected image's outcome is shown in Fig. 7. Table VII shows how well this technique performed.

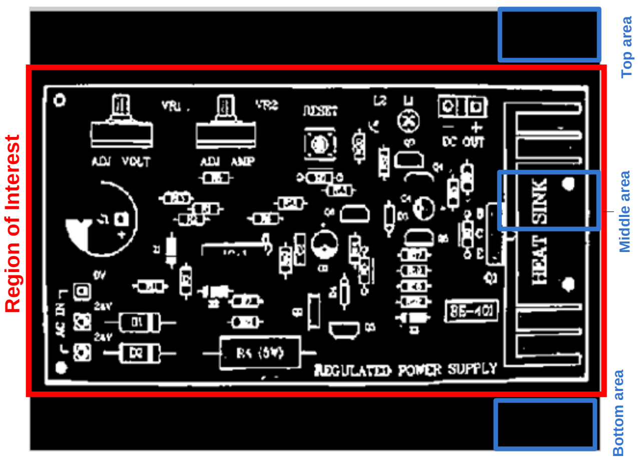

Fig. 7. The captured image.

TABLE VII. PERFORMANCE OF THE METHODOLOGY USED IN IMAGE ACQUISITION

Number of images	Number of Correct capturing	Performance of capturing step
211	207	98%

A. Image Segmentation Module

1) Board localization: The 8-connectivity component was utilized in this stage to sort every component found to be linked. Then, from the acquired picture displayed in Fig. 8, select the largest one among them based on its area, which is the entire board. The result of board localization is shown in Fig. 9. Table VIII shows the results of board localization.

2) Footprint segmentation: We cropped each footprint's bounding box depending on its coordination and the size of the PCB. Boxes with footprints for capacitors, variable resistors, integrated circuits, LEDs, and transistors are shown on the PCB in Fig. 10. The results of the segmentation process are displayed in Table IX.

B. Image Classification Module

The suggested AVIS model's performance was assessed in this study using the 207 photos for each proposed classification technique. Five different footprint kinds are included on each PCB. On the PCB, we fully show eleven footprints. The number of footprints on the PCB is displayed in Table X.

The boards include different kinds of uncompleted footprints as follows the footprints that are missed and four classes of footprints in percentage (25%, 50%, 75%, and 100%). Table XI shows the number of each class of footprint in 207 images.

The 207 photos are utilized in this manner, as indicated previously. One PCB has eleven (11) examined footprints. Production rule methodology is employed to execute real-time inspection in a real-world setting.

If the suggested system properly detects the form in a segmented picture, the accuracy value equals the percentage of footprints. Each component's footprint is assessed independently by the suggested segmentation. Finally, using the formula below, we demonstrate how the production rule performs for each footprint type.

$$Accuracy of\ production\ rule = \frac{\sum correct\ classification\ of\ footprints}{number\ of\ related\ footprints} \times 100$$

In the 207 photos, we counted the production rule accurate classifications, and Table XII shows the results. The final tables and figures, Table XIII and Fig. 11, show how the production rule performed.

In summary, an automated visual inspection technique for finding missing PCB components is presented in this paper. This study is built on pure image processing algorithms that offer effective and low-cost methods for representing and identifying defective PCB devices. A proposed production rule is used to classify the different sorts of faults. Additionally, template matching is used to identify the completed PCB footprints.

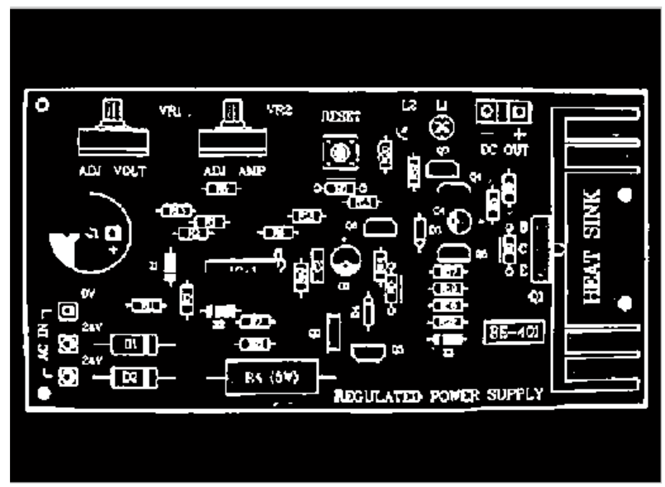

Fig. 8. The acquired image.

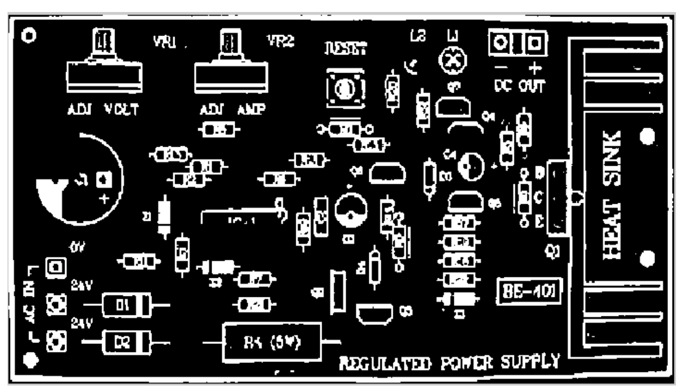

Fig. 9. The localized board.

TABLE VIII. THE PERFORMANCE OF LOCALIZING THE BOARD

Number of images	Number of Correct localizing	Performance of localizing step
207	207	100%

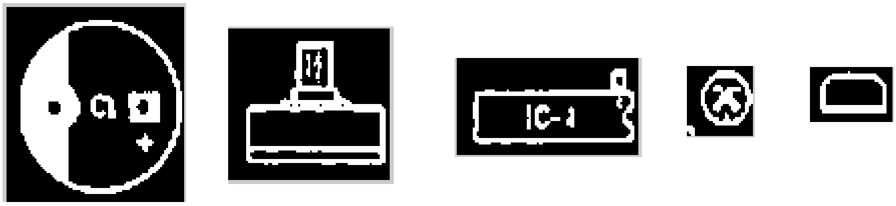

Fig. 10. The segmented footprints.

TABLE IX. THE PERFORMANCE OF THE IMAGE SEGMENTATION STEP

Number of segmented images	Number of Correct segmentations	Performance of segmentation step
2277	2214	97%

TABLE X. THE NUMBER OF FOOTPRINTS ON THE PCB

Number of image	Capacitor	Variable Resistor	IC	LED	Transistor	Number of footprints
1	1	2	1	2	5	11
207	207	414	207	414	1035	2277

TABLE XI. THE NUMBER OF EACH CLASSES OF FOOTPRINT IN THE 207 IMAGES

Type of footprint	25%	50%	75%	100%
Capacitor	23	69	46	23
Variable Resistor	23	92	23	253
IC	23	92	23	23
LED	23	46	46	207
Transistor	23	46	23	851

TABLE XII. THE NUMBER OF CORRECT CLASSIFICATIONS IN PRODUCTION RULE

Type of footprint	25% of footprint	50% of footprint	75% of footprint	100% of footprint
Capacitor	23	69	46	23
Variable Resistor	22	87	18	228
IC	23	89	23	23
LED	23	46	45	202
Transistor	19	37	19	813

TABLE XIII. THE PERFORMANCE OF PRODUCTION RULE

Type of footprint	25% of footprint	50% of footprint	75% of footprint	100% of footprint
Capacitor	100%	100%	100%	100%
Variable Resistor	96%	95%	78%	90%
IC	100%	97%	100%	100%
LED	100%	100%	98%	98%
Transistor	83%	80%	83%	96%

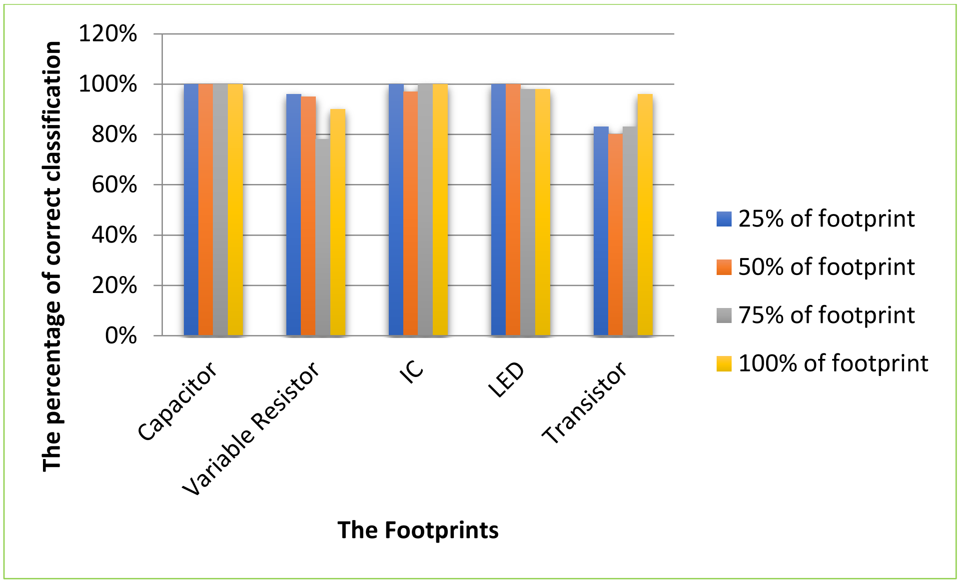

Fig. 11. The chart of performance of production rule.

V. Conclusion

This study presents a real-time automated visual inspection system using an image processing technique to detect the missing footprint components on printed circuit boards. This system consists of hardware and software components. The software involves pre-processing and post-processing stages. The capture step is finished, and the picture is segmented, localized, and extracted of its characteristics during the pre-processing stage. In order to categorize the footprints using the production rule, the post-processing step focuses on leveraging the feature extraction from the previous stage. Thus, we may conclude that the entire intelligent real-time machine vision system, whose design is presented in this study, can be utilized to enhance industrial quality control procedures.

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