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A NOVEL APPROACH TO AUTOMATED PCB QUALITY CONTROL: INTEGRATING IMAGE PROCESSING AND LARGE LANGUAGE MODELS

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Abstract

The integration of automated quality control technologies is nowadays a fundamental requirement for modern PCB production. This automated approach replaces manually based methods that are error-prone with fast, accurate and measurable estimates, helping to reduce the time and costs associated with traditional testing. Human inspection is less efficient, slower and overpriced than automated inspection. In this context, digital image processing, especially for the detection of defects such as faulty components or missing elements, becomes crucial. The production of printed circuit boards requires strict quality control to ensure the reliability and efficiency of electronic devices. Improving the detection and analysis of defects on printed circuit boards is as critical as ever. In addition to this, we propose the concept that combining classical computer vision techniques, such as edge detection and Kenny contour analysis, with large language models opens up innovative possibilities in defect identification.

The main function of the system is to comprehensively detect defects on printed circuit boards using automated visual inspection. It uses a digital camera to capture images of each PCB, which are then processed by a computer. This processing includes converting to greyscale and binary shapes, followed by an XOR operation to extract the necessary information. Contour analysis is then applied for classification. Incorporating language models into defect documentation and description is a significant step in automating quality control, as they can not only describe defects but also suggest corrective measures.

This system is capable of detecting various PCB defects such as missing components, incorrect polarity, open circuits and missing tracks. Its advanced fault detection and classification increase the speed and accuracy of evaluation, reducing human error, which is prevalent in quality testing, and introduces a usable fault and defect notification, detailed description and reporting system. Replacing manual testing methods with this new model significantly increases productivity.

Keywords: Image Processing, Printed Circuit Board, Defect Detection, Edge Detection, Classification system, Large language system.

Introduction

In the fast-growing electronics industry, the implementation of automated test systems is becoming increasingly important to ensure the quality of printed circuit boards (PCBs). This need is driven by the frequent occurrence of defects, mismatches and exposure errors in PCBs. Automated systems equipped with specialised defect detection algorithms significantly improve the quality and accuracy of PCB testing. These systems offer a marked improvement over manual testing, which often suffers from human fatigue, long test periods and increased operating costs.

Modern electronic component manufacturing technologies require efficient PCB design and test processes that meet stringent standards. Test efficiency and minimise human labour. An important step in improving the quality control of PCB production is the effective use of traditional computer vision methods for initial defect detection. Techniques such as Kenny edge detection and contour analysis are well suited to delineate object boundaries and highlight contours in PCB images. This initial stage identifies areas that require further investigation and helps to create a baseline dataset for further analysis. The next stage of defect detection involves the deployment of large-scale language models. These models, developed on the basis of advanced deep learning technologies, are capable of detecting and classifying defects, recognising their sizes, shapes and types. A significant advantage of these models is their ability to integrate textual descriptions of detected defects, enriching the documentation process. Using language models to analyse documentation and describe defects is an important step in automating and improving PCB quality control. Not only can they describe defects, but they also provide insight into potential corrective actions.

The combined use of traditional computer vision techniques and large-scale language models represents an integrated approach to PCB quality control. This methodology not only improves the accuracy of defect detection, but also reduces the probability of errors, contributing to the creation of a comprehensive system that automates the analysis and description of problems in printed circuit boards. This technological advancement is vital to improving production processes and is a key factor in the evolution of modern quality control methods in electronic manufacturing.

Background. Automated testing in PCB quality control, driven by fault detection systems and specialised algorithms, has significant advantages over manual testing, mitigating issues such as fatigue, long test times and high operating costs. However, there are certain limitations to consider. These include the potential for false positives and negatives, requiring accuracy in interpreting algorithms, and significant upfront investment in technology and infrastructure for implementation. Recognising these constraints is essential to achieving a balanced and effective strategy for controlling PCB quality through automation.

Objective. The central objective of this article is to investigate and verify the integration of state-of-the-art algorithms, such as including the Fault Detection Algorithm, Canny Edge Detection Algorithm, and Contour Analysis, within an automated PCB visual inspection system. The main focus is to demonstrate how the incorporation of large language models (LLMs) extends the inspection system, increasing its effectiveness. This research aims to highlight the highly effective synergies between advanced image processing techniques and LLMs, leading to efficient and accurate detection of a range of PCB defects, including missing components and circuitry issues. The end goal is to significantly increase the accuracy and efficiency of the defect detection process, thereby improving the overall approach to PCB quality control.

PCB quality control technologies. To ensure the production of high-quality final products that seamlessly conform to precise specifications, meticulous attention to detail is imperative. Testing teams within industries ardently strive to identify faults prior to product release, yet these faults often persist, even with the most rigorous manual testing processes. The implementation of automated testing methods emerges as the optimal approach to elevate testing efficiency and analysis [3]. Automated testing, particularly in the context of Printed Circuit Boards (PCBs), is instrumental in identifying common faults such as missing components, tracks, holes, and circuit breaks. Image processing plays a pivotal role in quality control for PCBs, not only facilitating defect identification but also expediting the evaluation of fault detection. This early detection mechanism enables timely corrections, thereby enhancing the efficiency of quality control procedures. Industries that integrate automated testing techniques reap the benefits of reduced testing times for product inspections [4]. Even with effective manual testing, defects in components can sometimes manifest after product delivery to customers, incurring wastage and additional manufacturing costs, or necessitating reevaluation. Recording and monitoring component readings and values via computer systems play a crucial role in maintaining product quality. By employing these methods, companies remain competitive by expediting the transition from concept to product, optimizing production workflows, and minimizing rejects during production [5]. Historically designed systems were primarily adept at detecting faults in bare Printed Circuit Boards, primarily identifying issues like broken tracks. However, these techniques are ill-suited for detecting faults in mounted PCBs, such as short circuits, missing components, and component polarities, which the proposed system effectively addresses. Moreover, these systems tend to be sensitive to variations in lighting conditions [6]. An article “Image Segmentation based on Edge Detection using Boundry Code” [7] classifies PCB defects into two categories: functional defects that impact the performance and quality of the PCB product, and cosmetic defects that affect the PCB's appearance, potentially influencing factors like heat dissipation and high-voltage current. In the proposed system, images are segmented, and defects are classified into distinct groups, such as square segments, hole segments, thick line segments, and thin line segments, each trained from template images. Notably, the system is constrained by its limitation to detect only these predefined defect segments [8]. A model suggested by Takumi Uemura [8] operates solely on grayscale images, potentially limiting its applicability. Future research aims to extend its functionality to color images and other types of images. The proposed approach incorporates the use of boundary code (BC) for edge detection, delineating edges within images as virtual edges within a virtual spatial context, with ongoing efforts directed towards adapting this method for RGB images. In this article I would like to emphasize on some of the methods namely: Fault Detection Algorithm, Canny Edge Detection Algorithm, and Contour Analysis in PCB quality control.

The Fault Detection Algorithm is a crucial component of PCB quality control, serving as an automated system designed to ensure the reliability and performance of electronic devices. This algorithm harnesses the power of advanced machine learning and computer vision techniques to systematically and accurately identify various defects present in printed circuit boards (PCBs). These defects can encompass a wide range of issues, such as soldering imperfections, component misalignments, micro-cracks, and structural damage. The algorithm's primary strength lies in its ability to efficiently and rapidly process large volumes of visual data, significantly reducing the need for labor-intensive manual inspections. By automating defect recognition, it enhances production efficiency and quality, making it an essential tool in the PCB manufacturing process. [9] The article “Enhanced PCB Defect Detection Using Canny Edge Detection” describes Canny Edge Detection Algorithm as a fundamental image processing technique employed in PCB quality control to identify and highlight edges and boundaries within PCB components. It excels at distinguishing edges from image noise, resulting in a precise representation of the PCB's structural features. In the context of quality control, the algorithm plays a crucial role in locating component outlines, verifying their alignment, and ensuring that the PCB layout conforms to design specifications. By enhancing edge detection, the Canny algorithm significantly improves the accuracy and reliability of defect identification in PCBs. [10] Contour Analysis is a fundamental technique in PCB quality control that involves the extraction and examination of geometric features within PCB components. It provides valuable insights into component alignment, dimensions, shapes, and orientation, enabling the verification of compliance with design specifications. Contour Analysis is instrumental in detecting manufacturing irregularities and ensuring that each PCB meets quality standards by assessing dimensions, shapes, and component orientations.

Within the framework of defect detection in printed circuit boards (PCBs), there is an exciting prospect of integrating large language models (LLMs). This advanced approach to interacting LLMs with previously discussed algorithms such as Fault Detection Algorithm, Canny Edge Detection Algorithm, and Contour Analysis brings the defect detection system into synergy, contributing to their synergistic enhancement. The use of LLM extends the functionality of the edge detection and contour analysis algorithms, which contributes to more efficient recognition and classification of various defects. The unpredictable ability of LLM to efficiently process large amounts of visual data opens up the prospect of significantly reducing the need for manual inspections, thereby increasing the accuracy of defect detection [11].

Focusing on the interaction of LLM with the Fault Detection Algorithm, there is an increase in the dynamics of the development of the PCB quality control system. The use of machine learning and image analysis inherent in LLM has significant potential to improve the accuracy and efficiency of detecting various defects. This includes detecting not only solder defects and missing components, but also isolated recognition of microcracks and structural damage.

Applied algorithms and methodologies. The proposed system employs several algorithms, including the Fault Detection Algorithm, the Canny Edge Detection Algorithm, and Contour Analysis and modern technologies of Large Language Models.

Fault Detection Algorithm. Input data comprises color images captured using a high-resolution 13-megapixel camera. The objective is the inspection of Printed Circuit Boards (PCBs) for faults, subsequently categorized.

The image processing algorithm proceeds as follows:

First, the two-dimensional RGB image undergoes transformation into grayscale. In the RGB color space, the color pixels—Red (R), Green (G), and Blue (B)—range from 0 to 255. Grayscale conversion entails merging these color channels, yielding a grayscale image. This amalgamation occurs when all three color channels manifest identical pixel values at corresponding coordinates. The grayscale value is computed as follows (1),

$$(R + G + B)/3 \tag{1}$$

Subsequently, the grayscale image undergoes a transformation into a binary image, where pixels are represented as either 0's or 1's, akin to a black and white image. A threshold value is established to interpret the pixel values. When the pixel value exceeds this threshold, it is set to 1 (white), while all other pixels are set to 0 (black). This binary conversion process prepares the image for defect identification. Following the image conversion, a bitwise XOR operation is performed on two binary images. This operation is true if one of the input values is true and false otherwise. The XOR operation is instrumental in the identification of defects. For the purpose of training the images of the PCB, Contour Analysis technique is employed. This technique involves a pixel-by-pixel examination of the entire image and serves the purpose of labeling faults. The results are subsequently generated to determine whether a sample image is deemed faulty or not.

Canny Edge Detection Algorithm. The Canny Edge Detection algorithm, as outlined in references [7] and [5], primarily serves for edge detection, with a focus on fulfilling three key criteria: a low error rate, good localization, and minimal response. The algorithm is applied to grayscale images, and it follows these steps:

The initial step involves removing noise from the image using a Gaussian filter. The Gaussian filter is a non-uniform low-pass filter designed to blur the images, resulting in a smoother image. This algorithm relies on a two-dimensional Gaussian function for image processing, which is mathematically defined as (2):

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

In the equation provided earlier, where x represents the horizontal distance from the origin, y signifies the vertical distance from the origin, and σ denotes the standard deviation of the distribution, it's important to note that this distribution is assumed to have a mean of 0. The next step in the Canny Edge Detection algorithm is to filter the smoothened image using the Sobel kernel. This process involves applying a pair of convolution masks in both the horizontal (x) and vertical (y) directions. The result of this operation yields information about the gradient strength and direction. The direction is typically rounded to one of four angles: 0, 45, 90, or 135 degrees. So Edge Gradient as next(3):

$$(\mathrm{G}) = \sqrt{G_x^2 + G_y^2} \tag{3}$$

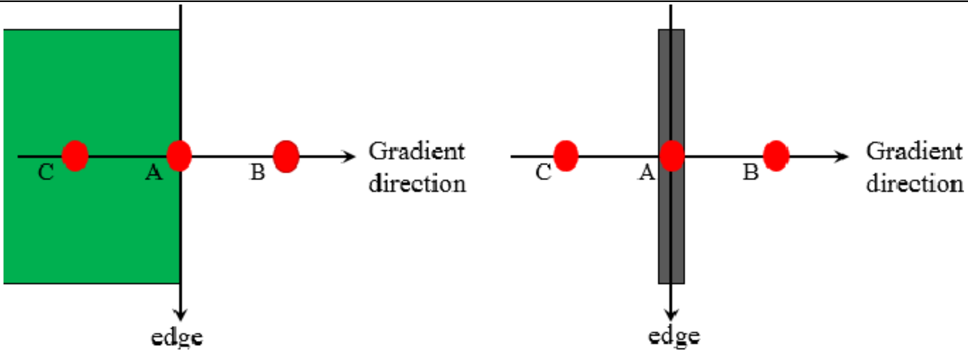
And Angle (Θ) (4):

$$\text{Angle } (\Theta) = \tan^{-1}(\frac{G_y}{G_x}) \tag{4}$$

Where, Gx is used to find intensity gradient along horizontal direction, Gy is used to find intensity gradient in vertical direction and angle (Θ) is used to calculate Gradient Direction.

The edges should be marked where the gradients of the image has large magnitudes.

After obtaining the gradient magnitude and direction, a comprehensive scan of the image is conducted to eliminate any extraneous pixels that may not constitute actual edges. To achieve this, at each pixel, it is examined to determine if it represents a local maximum within its immediate neighborhood in alignment with the gradient direction. This process helps in identifying and retaining only the essential edges in the image (Picture 1).



Pic.1. Non-maximum suppression

Point A is situated on the edge in the vertical direction, and the gradient direction is perpendicular to the edge. Points B and C are aligned with the gradient directions. Point A is subjected to an evaluation in conjunction with points B and C to ascertain whether it constitutes a local maximum. If it meets this criterion, it progresses to the next stage; otherwise, it is suppressed or reset. In summary, the outcome of the Canny algorithm is the generation of a binary image featuring "thin edges." The Canny algorithm employs two distinct thresholds, namely the upper and lower thresholds, to distinguish authentic edges from non-edges:

1. If the pixel's gradient value exceeds the upper threshold, the pixel is categorized as being on an edge.
2. If the pixel's gradient value falls below the lower threshold, it is rejected and not considered as part of an edge.
3. Pixels with gradient values that fall within the range delimited by the upper and lower thresholds are only considered as part of an edge if they are connected to a pixel with a gradient value exceeding the upper threshold. This ensures that only prominent edges are retained in the final output.

Contour Analysis. Within the PCB fault detection system, Contour Analysis plays a pivotal role in image recognition and fault labeling by analyzing various fault types. Contour Analysis allows describing, comparing, storing, and identifying objects based on their external outlines, or contours. A contour essentially represents the boundary of an object, effectively separating it from the background. It is postulated that the contour contains the essential information regarding the object, while the interior points of the object are excluded from the analysis. This selective focus constrains the algorithm's scope to the contour of the object, streamlining the Contour Analysis process. Contours enable a transition from the two-dimensional space of the image and are adaptable to varying image patterns while remaining invariant to transposition [12].

In contour analysis, the contour is written as a sequence of complex numbers. The starting point of the image is fixed on the contour. The contour is then scanned clockwise, and each displacement vector is denoted by a complex number a+ib. Where a is the displacement along the x axis, and b is the displacement along the y axis. Displacement is noted concerning the previous point. [13]

In the PCB fault detection system, Contour Analysis is specific to applicable area. In the binarized image, contours are selected and individual sections of the image are segmented. This allows for the training of various template images to detect contours and facilitates the process of searching for and comparing sample images with these template images. The objective is to identify the most similar portions of the image, aiding in the precise localization and characterization of faults in the PCB.

Contour Analysis within the PCB fault detection system significantly enhances image processing speed and overall performance. It provides a clear and accurate identification of fault areas, effectively labeling faults by analyzing their types and characteristics. This approach contributes to the system's efficiency and precision in fault detection and localization.

Large Language Models. Visual LLM. The model consists of multiple transformer layers, where each layer performs self-attention and summation operations [14]. This allows the model to interact effectively with different types of information and address language processing tasks.

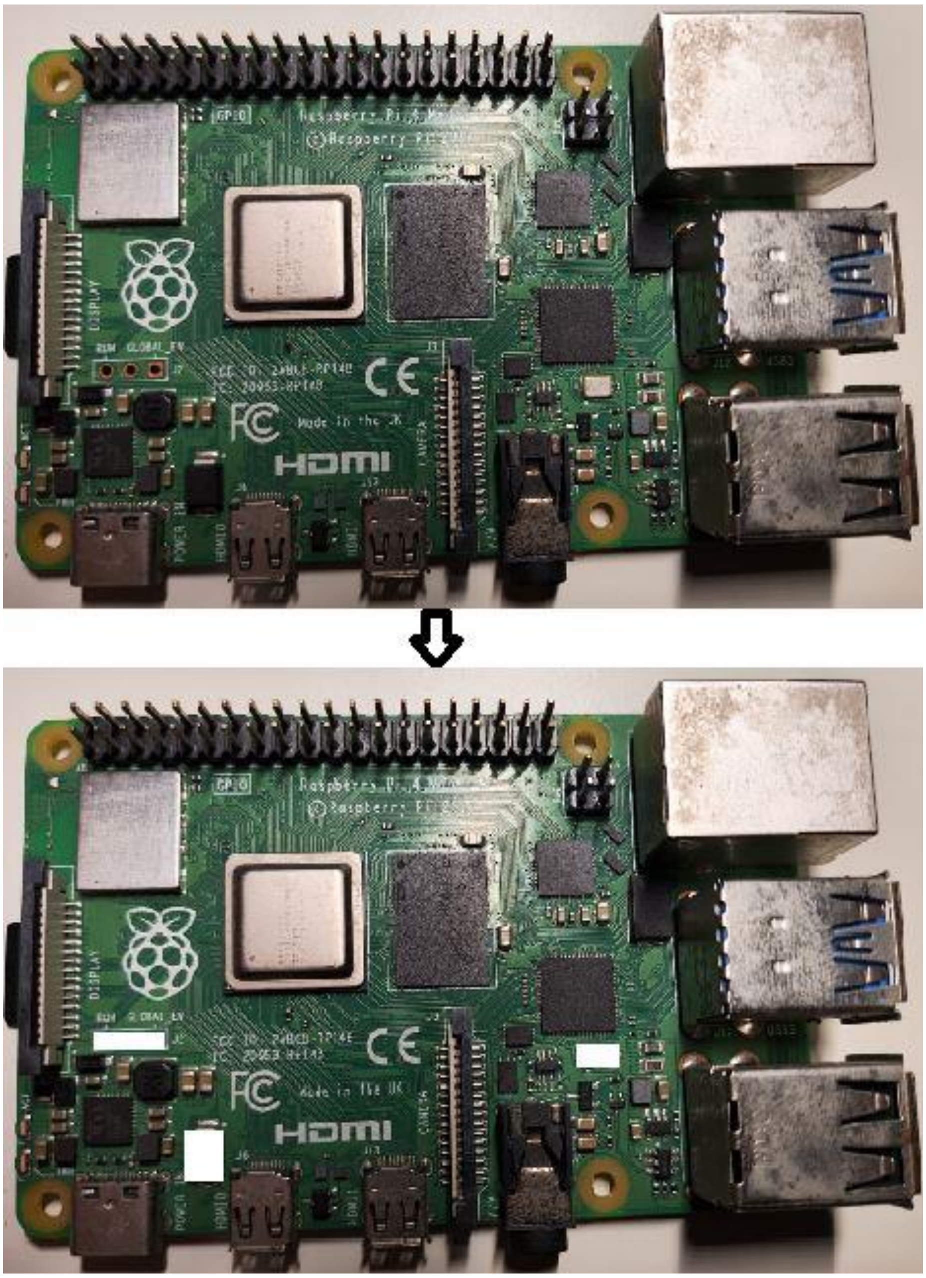
Another essential part of the algorithms is the training process. The model is trained on a large corpus of text data using deep learning methods. During training, the model determines weights for its parameters, optimizing them to maximize the accuracy of predictions.

A distinctive feature of large language model algorithms is scalability. They possess a high number of parameters, allowing them to tackle diverse tasks and comprehend a broad context. However, this scalability also results in a significant computational load, making their implementation computationally intensive.

It is important to note that the algorithms of large language models can be dynamically adapted to different tasks. The model can be fine-tuned or pre-trained for a specific type of input data or task, enabling their use in a wide range of applications. A drawback of these algorithms is the large number of parameters, which may lead to efficiency and computational cost challenges. Additionally, the potential emergence of biased or incorrect model outputs due to training deficiencies should be considered. The algorithms of large language models can be effectively integrated into quality control and defect detection tasks for printed circuit boards (PCBs). Leveraging the strengths of these models, such as their ability to comprehend contextual information and patterns, can significantly enhance the precision and efficiency of defect identification in PCB manufacturing.

One application is the analysis of documentation and specifications related to PCB design. Large language models can process and understand textual data, including design requirements, standards, and specifications. By integrating these models, manufacturers can automate the validation of PCB designs against industry standards and specifications, ensuring compliance and reducing the likelihood of errors in the early stages of production. Large language models can be employed for the interpretation of inspection reports and defect classifications. As part of the quality control process, these models can analyze textual descriptions of defects and corresponding images. This integration allows for a more comprehensive evaluation of defects, as the models can consider both textual and visual information to enhance the accuracy of defect identification.

Image processing experiment and results. A Raspberry Pi 4 microcomputer board was used to demonstrate the process and its results. The Raspberry Pi 4 is a small, affordable computer popular in education, hobby projects and research. It is known for its versatility, low power consumption, and the ability to work with a variety of operating systems. Picture 2 shows the printed circuit board (PCB) during testing, which serves as an input to the fault detection system. We then manually inject a visual defect onto the board, such as a visual spot, to simulate a defect in certain board elements, such as being missing or out of alignment with the physical dimensions.

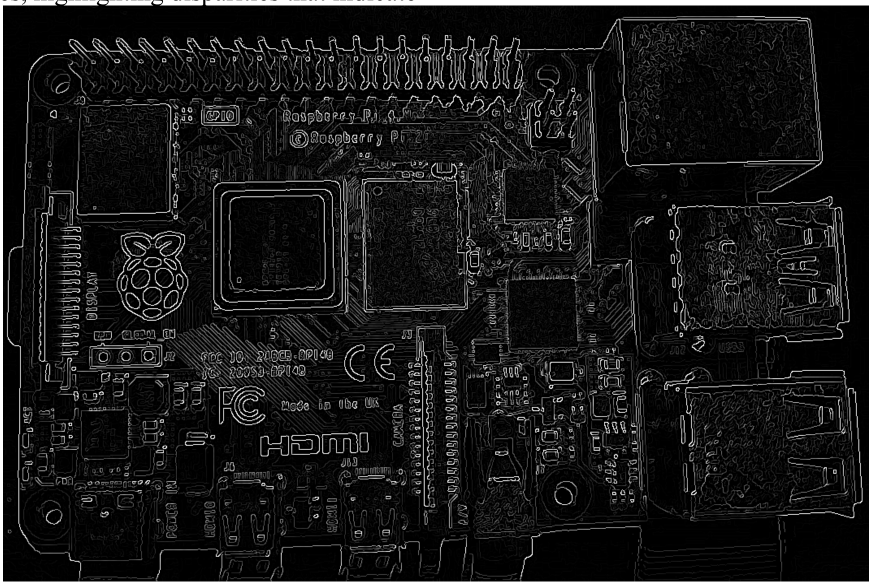


Pic.2. Template Image

In the described method, the template image is used as the initial input signal for the Canny Edge Detection algorithm. This process involves converting the template image to a binary format. This conversion is an important step to improve the visibility and distinguish the edges of the image. Picture 3 shows the result of this procedure: the template image after applying the Canny Edge Detection algorithm. It is important to note that before applying the algorithm, the template image is converted to grayscale, which is a necessary step to facilitate effective edge detection.

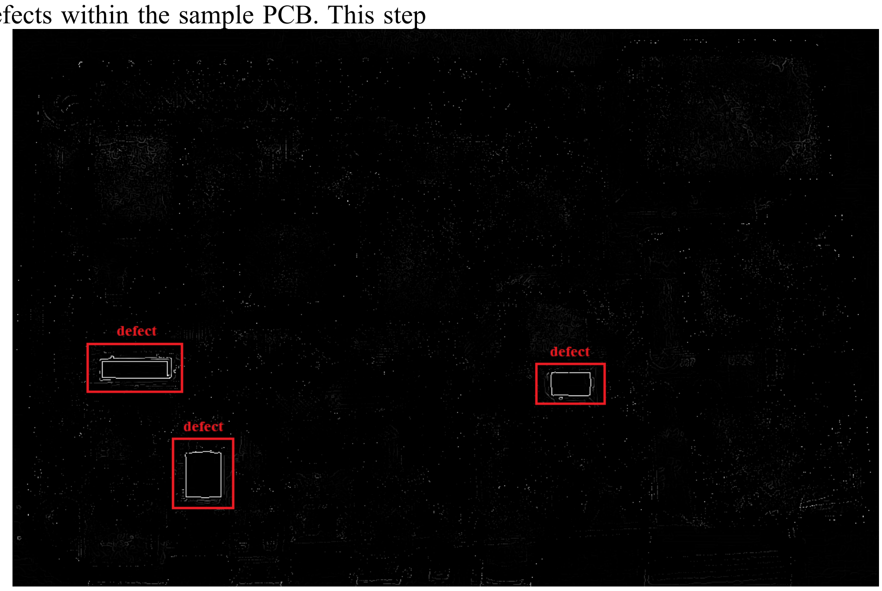
Following this, an exclusive-or (XOR) operation is methodically performed on two specific images: the processed template image and the reference image.

This XOR operation is a pivotal part of the defect identification process within the sample printed circuit board (PCB). It works by comparing the binary values of the two images, highlighting disparities that indicate potential defects. Picture 4 provides a graphical representation of the results derived from this XOR operation.



Pic.3. Results of Canny Algorithm

The visual output from this comparison effectively illustrates the discrepancies between the template and reference images, thereby revealing the existence and locations of defects within the sample PCB. This step is instrumental in diagnosing and analyzing the quality and integrity of the PCB, providing critical insights for further analysis and rectification measures.



Pic.4. XOR Operation

In the next phase of our research, we demonstrate the results of integrating visual large language models. This integration unlocks four key capabilities that are central to our research:

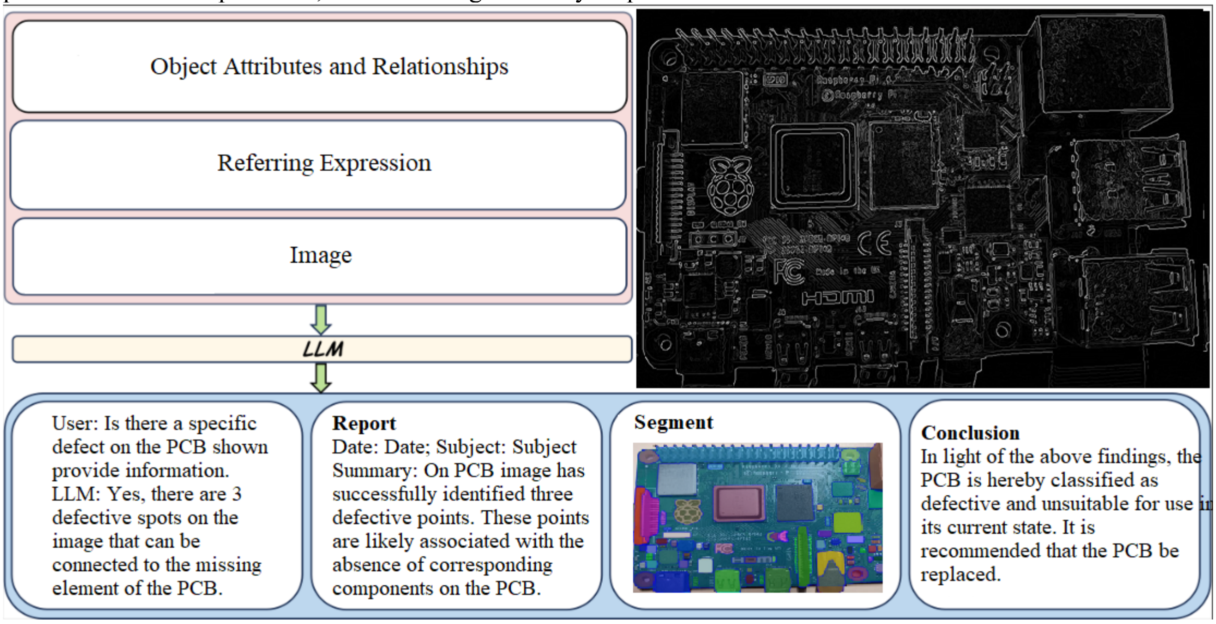
1) Direct use of these models for advanced defect evaluation: This approach allows us to conduct in-depth analysis, identifying both the type of component and the nature of the potential defect.

2) The ability to generate and send detailed reports: This feature is particularly useful for communication and documentation. It allows you to automatically generate comprehensive reports to specific stakeholder needs or documentation requirements. This not only simplifies the reporting process, but also ensures that all relevant information about defects and their consequences is communicated accurately and efficiently

3) The ability to segment an image to isolate elements: This feature plays a crucial role in accurately identifying and isolating individual image components. By segmenting the image, the system can focus on specific areas or elements, allowing for a more targeted and detailed investigation.

4) Making the final decision on the quality of the PCB.

Picture 5 shows the system response based on the operational functionality of these integrated large language models. This image illustrates the practical application of these capabilities, demonstrating how they specifically contribute to the analysis and evaluation process in the context of PCB assessment.



Pic.5. Response based on the operational functionality

Conclusion. The implemented system consistently provides accurate test results for printed circuit boards (PCBs). Its effectiveness lies in the ability to qualitatively determine the presence or absence of faults in PCB samples. The results obtained are systematically classified based on the different categories of faults observed in the PCB samples. These categories include defects such as missing components, polarity reversal, open circuits and missing tracks. Comprehensive reports are systematically generated to document the frequency of faults found in PCBs. To further improve the accuracy of the results, the system uses Large language models, which allows for the expansion of the functionality of PCB quality assessment. Further improvements can be made by using 3D images to detect complex defects such as solder joint quality and solder thickness.

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