Image-Based Detection and Classification of PCB Defects

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Abstract Printed Circuit Boards (PCBs) are becoming increasingly fundamental and complex in the modern age, necessitating complex systems for quality control. Recently, advances into dataset collection and machine learning have made new techniques viable when compared to more traditional ones. This paper proposes an Image-based defect isolation and classification method utilising Bag of Knowledge and SVMs.

1. Introduction

Printed Circuit Boards (PCBs) are fundamental to the functioning of modern electrical and computer based systems, and are present in everything from toasters to supercomputers. In the production of PCBs, it is possible for PCBs to be created with defects that hinder the functionality of the board, due to slight imperfections and variability in the manufacturing systems and processes. These could range from minor abrasions that decrease the efficiency of the board, to disconnected components that render the electrical functionality of the board useless. Therefore, a need exists to exert quality control in the manufacturing process, and identify defections in PCBs to ensure only functional boards are brought to market.

Manual approaches are not feasible due to the visual complexity of PCBs, and automatic detection is becoming more difficult as PCB complexity continues to increase. The principles outlined in this research are not only applicable to PCBs, however. In fact, there is a growing need for intelligent and automatic systems for defect identification in a wide range of manufacturing processes, especially as products become more complex and production volume increases. To this effect, the papers reviewed below explore image classification and identification in the realm of PCBs, which may offer insight into implementing novel machine learning based approaches. Namely, this paper aims to re-implement the defect isolation techniques in (Huang & Wei, 2019), and use a classifier inspired by (Kumar et al., 2017). This will enable a better understanding of image processing techniques and CNN machine learning models in the realm of PCB defect detection.

2. Review of Implementation Paper

(Huang & Wei, 2019)

2.1. Storyline

Problem and Motivation

The heightened complexity of modern printed circuit boards (PCBs) has revealed the critical need for robust defect identification and classification methods within the electronics manufacturing industry. As PCB designs become increasingly intricate, the task of manually scrutinizing and categorizing defects has become more challenging and time-consuming. In response to this challenge, recent research efforts have turned towards leveraging advanced machine learning models to automate and optimize defect detection processes, as opposed to traditional image classification based methods. However, the efficacy of these models heavily depends on the availability of large and diverse, but standardized, datasets for training. This paper aims to address this need, as well as demonstrate the the utility of new data in the development of a machine learning model for image-based classification of PCB defects.

Prior Work

Various methods have been proposed to implement automatic visual image-based defect identification. One approach utilized an elimination-subtraction method which directly subtracts a reference image, which is the PCB as it should look like, from the inspection image, the image of the manufactured PCB to be examined for defects. It then conducts an elimination procedure to locate defects in the PCB (Wu et al., 1996). Another approach also used a reference-inspection method like the one above. It caught defects by getting properties of both the reference and inspected images, such as the number of connected regions, Euler numbers, areas, and identified defects that way (Zheng-Ming et al., 2012). A non-reference approach utilized a neural network paradigm, in which various defective patterns representing corresponding defect types were designed and thousands of defective patterns had been used for training and testing (Heriansyah et al., 2003). There have been other approaches as well, but the aforementioned methods give a broad overview of the research into image-based PCB defect detection.

Research Gap

Conventional approaches to PCB defect detection typically have not utilized any learned features, but are instead based on handcrafted knowledge and image processing for the identification of defects. As research interest in this field has increased, the interest in utilizing more powerful machine-learning based approaches has led to the necessity of large usable datasets for model training. However, the lack of quality and standardized publicly-available datasets of PCBs with manufacturing defects has hindered the development of more advanced machine-learning based approaches when compared to conventional approaches. This demand is now being answered, and newer techniques are now being explored.

Contributions

As mentioned in the above section, there is a need for good image datasets of PCBs with manufacturing defects in order to train and utilize machine-learning based models. The paper that is subject of this work has addressed that need by publishing a dataset of 1386 images with 6 types of identifiable defects for the use of detection, classification, and registration tasks. In addition, the paper has proposed a modification to the conventional approach to defect detection which is detailed in the section below. These innovations lie in the defect isolation and classification processes.

2.2. Proposed Solution

As mentioned in the Research Gap section, conventional approaches to PCB defect detection rely on pixel-by-pixel image processing that is computationally expensive, and handcrafted knowledge that has a more limited ability to detect defects and is less scalable. The proposed solution of the paper bypasses the need for both of these approaches. A preprocessing and isolation system is able to isolate the PCB defects and reduce amount of data needed to determine defects when compared to conventional approaches. A Convolutional Neural Network (CNN) is used to classify the defects. The training of the CNN allows the model to learn identifying features of the defects that may not be captured in the handcrafted knowledge approach.

2.3. Claims-Evidence

Claim-Evidence 1

The paper claims that defect location using their preprocessing and detection method is highly accurate. Of course, 'highly' is a relative term - so let us say that the threshold accuracy for each category of defect should be greater than 90%.

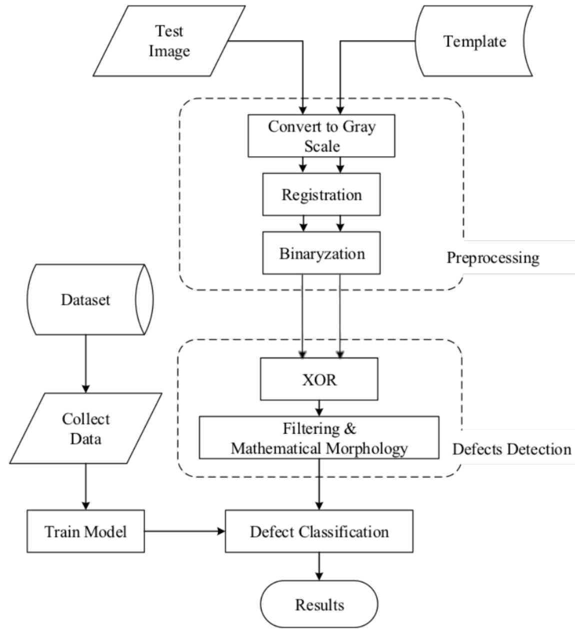

Figure 1. Process Diagram of Proposed Solution

TABLE IV

DEFECTS DETECTION RESULTS, FIRST ROW LISTS NUMBER OF DEFECTS PROVIDED BY DATASET, SECOND ROW LISTS NUMBER OF DEFECTS GOT BY OUR METHOD, AND THIRD ROW ARE THE ERROR RATE P_DS.

	Missing hole	Mouse bite	Open circuit	Short	Spur	Spurious copper
Actual number	497	492	482	491	488	503
Detected number	497	493(+1 error)	483(+1 over lapped)	491	488	503
Error rate (P_d)	0%	0.2%	0.2%	0%	0%	0%

Figure 2. Summary of Defect Detection Results

As shown in Figure 2, Every Missing Hole, Short, Spur, and Spurious copper throughout the dataset was correctly identified as a defect, meaning an accuracy of 100%. Only one extra Mouse Bite and Open Circuit was falsely detected as a defect, meaning an accuracy of 99.8%. Therefore, the claim is validated.

Claim-Evidence 2

The paper claims that defect classification using their preprocessing and detection method is highly accurate. To clarify, once the potential defects are located in the test data they are classified. Of course, 'highly' is a relative term - so let us say that the average accuracy across the 6 type of defects should be greater than 90%. The paper states that the average accuracy across the 6 type of defects is 97.74%, thus proving the claim.

Claim-Evidence 3

The paper claims that the registration step of the PCB inspection process (see Section 1.2) takes the most time compared to the other steps.

TABLE VII
TIME CONSUMPTION OF EACH STEP, REGISTRATION TAKES UP THE MOST TIME, FOLLOWED BY LOCALIZATION AND BINARYZATION.

Procedure	Time(s)
Registration	0.6219
Binaryzation	0.1650
Localization	0.1808
Classification	0.0212
Total	0.9889

Figure 3. Average time for each Step in the Inspection Process

The Registration step indeed takes the most time, 0.619s on average, as shown in Figure 3 - so the claim is valid.

2.4. Critique and Discussion

A particularly useful insight of the paper is the method by which it isolates the defects before running the classifier on the isolated defects. Rather than slicing the whole PCB image into chunks, and running the classifier in each chunk to identify defects, a reference image is used to isolate only the parts of the PCB that differ, thus drastically reducing processing time. Of course, this requires an ideal reference image. However, obtaining the reference is not to difficult, all that is necessary is to image a defect-less PCB. This being said, the paper's details on the registration and filtering steps are sparse and not precisely articulated. In my own implementation, following their general guidelines resulted in noise and false-positive defects being identified. That being said, at least from for the non-rotated defective PCBs, their algorithm for isolation and classification works with near 100% accuracy, which matches the claims and results in the paper.

3. Review of Supporting Paper 1

(Kumar et al., 2017)

3.1. Storyline

Problem and Motivation

As discussed in the previous paper, much effort has been put towards the detection of PCB defects in a manufacturing setting for the purposes of quality control. These efforts can be broadly organized into three distinct categories: Referential, Non-Referential, and Hybrid approaches. In the Referential approach, defects are isolated by taking the test PCB image with potential defects and subtracting it from a reference PCB, which is the ideal image of the PCB without defects. The corresponding area is the difference from the ideal, and hence potential defects. However, the subtraction step requires the images to be in as similar an environment as possible, i.e. rotation, translation, lighting, etc. If these are not the same, these factors could introduce significant noise, and therefore false positives in defect isolation. The Non-Referential on the other hand does not require a reference image, and defects are isolated through extracted features on the test image, which can take a variety of forms but are usually tied to image properties. The Hybrid approach is obviously a mix of both the Referential and Non-Referential approaches. This paper proposes a Non-Referential approach to PCB defect detection.

Prior Work

Various approaches have been utilized for Non-Referential approaches that differ significantly due to the variety of feature identification methods. One approach utilized a Bag of Keypoints (BoK)and Support Vector Machine (SVM) as a classifier. A Visual Word dictionary (VWD) was formed of RootSIFT features from whole image using the BoK. BoK Histogram features are then used for SVM learning and classification (Inoue et al., 2015). Another method utilized a boundary analysis technique to detect small faults by using Freeman Chain Coding. In this method first Euclidean distance and boundary distance of two boundary points are compared which are at a constant number of chain segments apart (West et al., 1982).

Research Gap

As indicated in prior sections, research into Referential methods has been more common due to ease of processing and training. Non-Referential approaches are often more technically complex, but have the advantage of more adaptive and versatile capabilities defect to isolate and classify defects. In a manufacturing setting, these qualities are more desirable due to real-world variance. Additional research into Non-Referential approaches may also complement Hybrid approaches, as those methods do utilize some Non-Referential techniques.

Contributions

This paper contributes to a more thorough understanding of Non-Referential approaches and how it may compare to prior attempts. In addition there are several novel techniques used that will be elaborated upon in later sections. Namely, the segmentation of of the PCB image by material and the usage of an SVM. It is also important to note that there is difference in the types of defects detected, as the identified defects in this paper are small defects such as dust and discoloration, which differ from the types of defects identified in the previous paper.

3.2. Proposed Solution

The test PCB image is first segmented into Copper and Non-Copper segments. Each segment will undergo its own defect isolation pipeline. The Copper segment undergoes a Hugh Circle Transform, upon which the circular features are extracted. A 1vR type SVM is applied to the edges of the circular feature to obtain the defect class. The Non-Copper segment first has a 3D non-uniform color histogram

Model	True Defect		Pseudo Defect		Accuracy(%)
	Correct	Incor.	Correct	Incor.	
Paper[8]	496	104	452	148	79.0
Paper[1]	532	68	572	28	92.0
Proposed	711	48	309	7	94.88

Figure 4. Primary Results Table for Paper Methodology

extracted from it, and the Non-Copper pixels are sorted into the histogram bins. An SVM with a polynomial kernel is applied to obtain the defect class. Once both defect classes are obtained, the Final defect class is determined through a logic conditional based on handcrafted knowledge.

3.3. Claims-Evidence

Paper[8] is a previous non-referential approach using SVR and Paper[1] used a similar method to this paper, that is the Hugh Circle and Histogram, without the SVM.

Claim-Evidence 1
The paper asserts that the accuracy of this methodology is comparable to prior attempts. As shown in Figure 4, the overall accuracy of the method is superior to prior Non-Referential methods, which validates the claim.

Claim-Evidence 2
The paper also claimed that further insight would be generated to draw conclusions relative to prior models. The SVM approach is shown to be particularly promising, as it has significantly higher overally accuracy than the SVR method and the histogram method of prior papers. This would suggest SVMs are particularly reliable when paired with the Hugh Circle and Histograms for isolation, thus validating the claim.

Claim-Evidence 3
The paper stated that the accuracy of the Copper segment should be comparable to that of the Non-Copper segment. The deficit-type defect was less accurate in the Copper portion than in the Non-Copper portion. This was due to random error and unpredictability in the chunking/separation of the Copper and Non-Copper segments. Thus, the claim is invalidated.

3.4. Critique and Discussion

The paper does propose a very different and novel model when compared to the prior Non-Referential and Referential approaches, especially the idea of separating the Copper and Non-Copper portions before classification. However, the paper was not very clear that the defect areas had to be 'chunked' to isolate the regions surrounding the defects first. This adds computational complexity and biases the model towards detecting smaller defects. Perhaps this method could be modified with addition image processing, such as conversion to gray-scale or binary, which may simplify the edge detection and classification.

4. Review of Supporting Paper 2

(Zhao et al., 2022)

4.1. Storyline

Problem and Motivation
The field of PCB assurance, which is more broad then just specific defect detection, has benefited from the introduction of Machine Learning (ML) methods in recent years, as conventional Computer Vision (CV) methods fall out of favor. That being said, the new ML models have certain disadvantages such as high data requirements and low adaptability. To overcome these deficiencies, the answer may lie in more advanced CV methods as opposed to ML methods. These CV methods may allow feature reduction, thus making ML models easier to train. They may also easily extract or isolate complex features, allowing more complex ML models to do more complicated tasks with PCB images. In particular the paper focuses on the extraction of PCB image features for the purposes of PCB component isolation.

Prior Work
Prior research into the performance of CNN architecture in the object recognition field found that image texture features are more significant than object forms in object detection. Other papers have indicated that a mixture of image color features with form features produce accurate results for object detection. More generally, research has indicated that CV feature extraction has the potential to significantly improve the viability of ML models to detect more complicated features through dimensional reduction.

Research Gap
Despite some renewed interest in the usage of CV methods for the purposes of feature extraction in the general field of object identification, there have been few attempts to apply them in the domain of PCB assurance. CV feature extraction methods have even been used for identification and isolation tasks in other quality assurance areas such as metalwork and pharmaceuticals. These objects are more or less very regular and it is an easier task to identify defects or isolate parts. PCBs by contrast are highly heterogeneous, compact, and irregular in nature, which makes object detection/isolation more difficult. Hence, the need of this paper to explore effective CV methods for component detection.

Contributions

This paper explored 34 CV methods to effectively extract PCB image features such as color, shape, and texture. It also evaluated them to find the best methods to achieve a particular feature extraction. It also determined the significance of these extracted features for the purposes of for PCB component detection. For example, it found that the color feature has particularly good performance in extracting the PCB components. More information about the findings are included in the Results section.

4.2. Proposed Solution

First, the PCB image dataset was preprocessed by performing a variety of operations such as color correction, region windowing, semantic data generation, etc. The preprocessing operations are numerous since there are many CV methods being utilized, which each have particular preprocessing requirements. These processed images are now passed into the CV methods for feature extraction. Of the 34 CV methods, 13 are for color extraction, 12 are for shape extraction, and 9 are for texture. Finally, the extracted features are run through a Random Forest for feature selection and analysis.

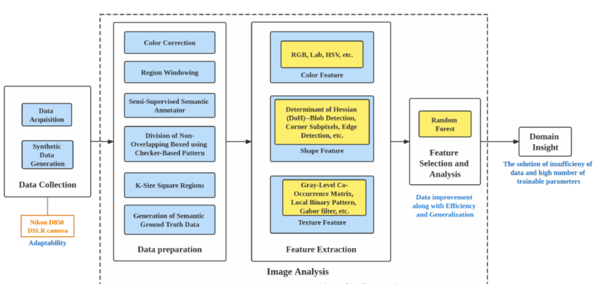

Figure 5. Process Diagram

4.3. Claims-Evidence

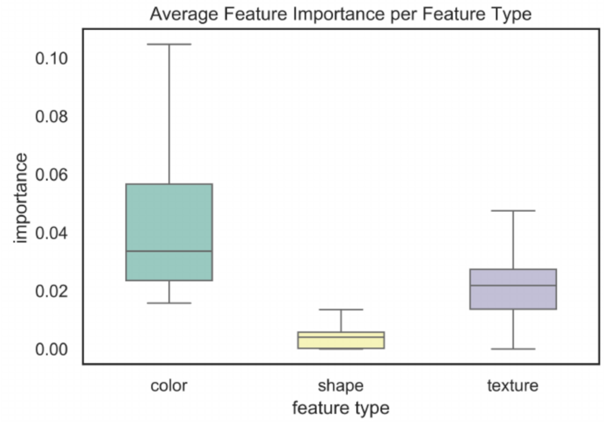

Figure 6. Box Plot of the 3 Features' Importance for PCB Component Detection

Claim-Evidence 1

The paper made the claim that the color feature is significant to object detection. This claim seems to hold for PCBs as well. The box plot in Figure 6 shows that among the color, shape, and texture features, the color feature has the highest median importance in its ability to map the detection of PCB components.

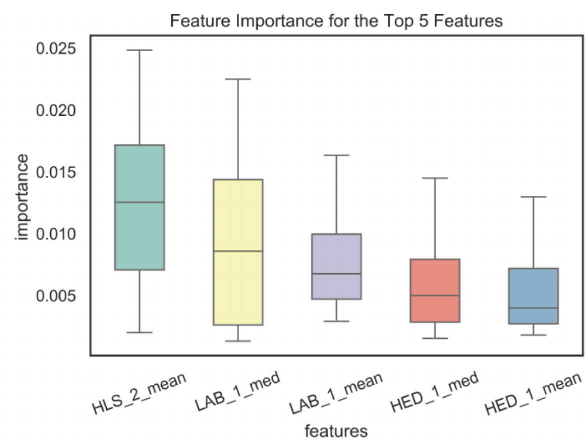

Figure 7. Box Plot of the 5 Most Significant Feature Channels

Claim-Evidence 2

The paper made the claim that the significance of the color feature comes from the contrast of the PCB background color, usually green, to the color of the components (varied). If this is true, we expect that the individual color channels would have the most significance in the detection of PCB components. As per Figure 7, all of the 5 most important feature channels were all extracted from the color feature, thus validating the claim.

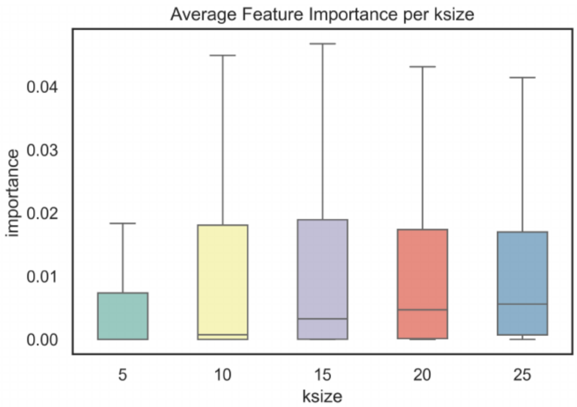

Figure 8. Box Plot of the Experimental Window Sizes' Importance

Claim-Evidence 3
The paper made the claim that smaller window sizes are very unfavorable for extraction of the shape and texture features. For example, it is difficult for a small region in the shape feature to reflect the lines and corners. From Figure 8, we can see that a ksize of 25 is the best, since it has the highest median and shorter range. Meanwhile, a ksize of 5 is the worst as it has the lowest median and range. Therefore, the claim is validated.

4.4. Critique and Discussion

This paper has several broad insights that extend beyond PCB component shape isolation, and relate to the identification and isolation of defects. For example, the paper showed that the texture feature is not as great for component identification, but it has higher significance for defect identification. The color feature extraction could be useful for the Hole or Pad type defects. That being said, the paper does not go into much detail about the individual feature channels and how those were extracted. This would make it harder to utilize these insights in other implementations. The methods used in this paper could also be used to extend an existing PCB defect classification model, since most operate on un-soldered PCBs without components. Extracted shape data could be used to train a model to classify incorrectly soldered components. for example.

5. Implementation

5.1. Implementation Motivation

This paper will aim to re-implement the PCB image-based defect isolation method in Section 2, more specifically shown in Figure 1. The authors of that paper did not publish their code, and understanding how to actually implement their methodology will enable a better understanding of the image processing techniques used, as well as the potential to extend the methodology in the future. The classification portion of that paper's model will instead be replaced an general implementation of the Bag of Features (BoF) and Support Vector Machine (SVM) methodogy from Section 3. The motivation behind this substitution is to try a model that is known to work in a non-referential context and explore its viability in a referential context. The results will be compared to the CNN classifier model originally used. This all being said, since the precise code used is not provided for either paper, it may be possible, even likely, that this paper's implementation differs from theirs somewhat. This paper may also alter the original methodology based on intermediate results during the implementation process, if a different technique is found to be more effective.

5.2. Implementation Plan and Setup

The data utilized in this implementation will come from the main implementation paper dataset provided by (Huang & Wei, 2019). As mentioned above, a BoF and SVM will be the defect classifier methodology. The BoF will use SIFT for feature extraction and k-Means clustering to create the BoF. The SVM will be a linear SVC, and will classify 0-5, each value representing a defect class present in the dataset.

This model needs to be trained. Given the large dataset, image size, long training times, and limited computational resources, only a portion of the data will be used for training. This must be kept in mind for this method's results, as the model from the main implementation paper was trained on a much larger set of defects. The defective PCB images have a corresponding XML file that contains annotation information with the defect class and corresponding rectangular bounds for each defect in the image. Using the annotation, the defects will be extracted and normalized to a 64 x 64 standard resolution, which will then be used to train the SVM. A training accuracy score will be determined.

The trained model will now meed to be tested. The method will be tested on the same dataset, using referential methods outlined in Figure 1. The defective PCB will be compared to the reference to isolate defects, at which point the SVM will predict on the defects to determine their class. Quantitatively, an an accuracy score will be determined for the given PCB as a percentage of defects correctly classified. This procedure will be run on several PCBs from each defect class, allowing an average accuracy score for each defect class to be determined, since each PCB image in this dataset has only one type of defect class on it. A qualitative assessment of general performance, noise, etc. will be made.

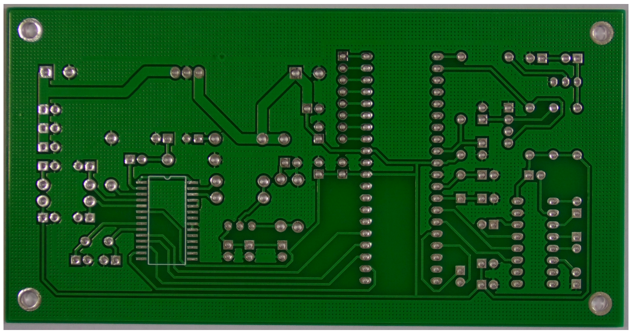

Figure 9. Sample Reference PCB

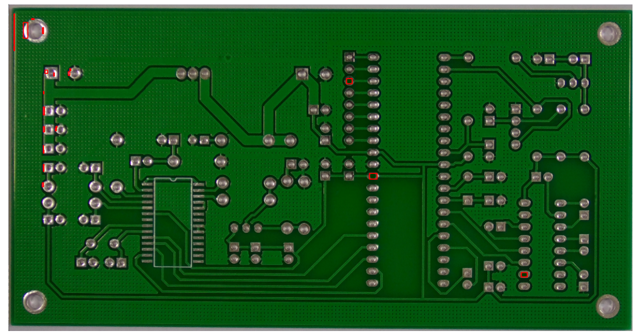

Figure 10. Sample Output of a Defective PCB Passed through Defect Isolation.

5.3. Implementation Details

For this implementation, the main libraries used were OpenCV, Scikit-learn, and numpy. Numpy was useful in general to handle arrays, OpenCV was primarily used for image processing, and Scikit-learn was used for the BoF/SVM. As mentioned before, none of the papers had publicly and freely accessible code to reuse in this implementation. Thus, the defect isolation and BoF/SVM had to be re-implemented. That being said, there was general example code available on the internet that I looked to for guidance in the implementation. In particular, the documentation of Scikit-learn and OpenCV were useful to understand BoF, SVM, and image registration.

5.4. Results and Interpretation

The SVM was trained on 341 individual extracted defects, with an overall training accuracy of 78.26%. This accuracy can be raised much higher by extracting more defects for training, as it was observed that as more defects were added to the training pool the accuracy would consistently increase. Unfortunately, as mentioned earlier, limited computational resources and time were available for training, which limited the amount of defects to train on. It should also be noted that the distribution of the training defects across the defect classes was not equitable. For example, there where 15 more Mouse Bites than Holes.

This paper's implementation of the defect isolation had significant noise compared to the original paper's implementation, as seen in Figure 10. The noise is almost entirely due to rotation or tilt in the defective image, as it was observed that no noise is present when rotation/tilt between the two images are equivalent. This would suggest an issue with the image registration, as that is the functionality responsible for feature mapping to correct rotation, though partial fault may lie in the filtering. As a result, this noise tanked the accuracy of the SVM model on the testing dataset, as the SVM was predicting on noisy data. This makes it extremely hard to gauge the actual testing performance of the model. Through hand-selected selection of particular defective PCB images that have no noise, a rudimentary estimation of accuracy for each defect category was determined.

Table 1. Ambiguous Results of SVM Testing Accuracy

Defect Categories	accuracy
Missing Hole	84%
Mouse Bite	62%
Open Circuit	74%
Short	78%
Spur	67%
Spurious Copper	75%

Table 1 details the spurious results of the testing. It is interesting to note that the Hole accuracy is the highest. This would make the most sense as it is by far the most visually distinct feature compared to the other defect classes.

6. Conclusion and Discussion

It seems that the method proposed in this paper does hold promise. However, increased computation power is necessary for better training of the SVM, and the reason for the noise in the defect isolation needs to be solved to make the proposed methodology viable. Only then can a proper evaluation of the methodology can take place in comparison to the original paper's implementation. Regardless, the insight gained will help greatly in advancing the field of Image-based PCB defect detection.

References

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