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Using Deep Learning for PCB Fault Detection

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Abstract: *Electronic components are mainly connected to one another using printed circuit boards, or PCBs. This phase holds significant importance in the production of electronic goods. The finished product may become unusable due to a minor PCB flaw. As a result, throughout the PCB manufacturing process, rigorous and thorough flaw identification procedures are essential. To guarantee the dependability and performance of electronic products, quality control and assurance procedures are essential in the electronics manufacturing process, especially when producing printed circuit boards (PCBs). Conventional inspection techniques are not always effective in locating different kinds of PCB flaws. Defect identification is essential to guaranteeing the dependability and functionality of electronic products since printed circuit boards, or PCBs, are essential parts of electronic gadgets. Conventional approaches to PCB defect detection, like manual inspection or traditional image processing methods, are frequently laborious, imprecise, and prone to human error. This research suggests utilizing the YOLOv5 model, a cutting-edge deep learning-based object detection technique, to create an automated PCB flaw detection system in order to overcome these difficulties.*

Keywords: PCB; flaw; identification; in-depth knowledge.

I. INTRODUCTION

In order to detect five different sorts of defects missing holes, short circuit, open circuit, mouse bite, and spur-this project will employ deep learning to develop a YOLO-based defect detection system. The system's objective is to improve the speed and accuracy of PCB inspection by employing sophisticated computer vision techniques. This will ultimately help to decrease the time-to-market for electrical devices and improve production quality.

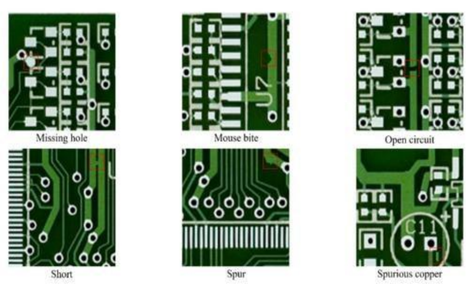

Figure 2. Examples of PCB defects.

1.1 Types of Defects:

A. Missing Holes:

- **Description:** Missing holes occur when the drilled holes that should be present on the PCB are not created. These holes are essential for the placement and soldering of through-hole components.
- **Detection:** Visual inspection or automated optical inspection (AOI) can identify areas where holes are absent but should be present.

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B. Short Circuit:

- **Description:** A short circuit in a PCB happens when two or more conductive paths that should be electrically isolated are unintentionally connected, allowing current to travel along an unintended path.
- **Detection:** Electrical testing methods, such as continuity testing or flying probe testers, can detect shorts. AOI systems can also identify physical bridges between conductive paths.

C. Open Circuit:

- **Description:** Open circuits occur when there is a break in a conductive path, preventing the flow of electrical current. This break can be due to incomplete etching, cracks, or breaks in the copper traces.
- **Detection:** Continuity testing and in-circuit testing can help identify open circuits. AOI can also spot gaps or breaks in the traces.

D. Mouse Bite:

- **Description:** Mouse bites refer to small, semicircular notches along the edge of a PCB, typically where breakaway tabs or perforations are used to separate individual boards from a larger panel.
- **Detection:** Visual inspection is usually sufficient to identify mouse bites. Automated systems can also detect irregular edges.

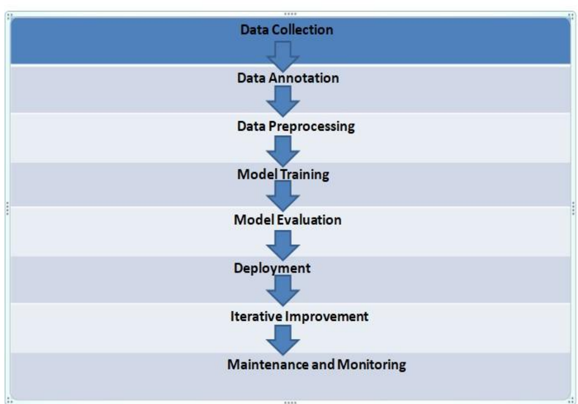
E. Spur:

- **Description:** A spur is a small, extraneous piece of conductive material extending from a trace, resembling a spur or a small projection. Spurs are usually the result of manufacturing defects during the etching process.
- **Detection:** AOI systems are well-suited for detecting spurs, as they can identify deviations in the trace geometry.

II. METHODOLOGY

Outlining the key elements and procedures in the process is necessary when creating a block diagram for a PCB flaw detection system utilizing the YOLO v5 model. To help you with the setup, here is a high-level block diagram. With this high-level block diagram, we see the methodology for our project with clean description each steps.

FLOWCHART



2.1 Data Collection:

Compile a varied dataset of pictures that includes both PCBs with no errors at all and PCBs with a range of defects, including component misalignment, soldering problems, open circuits, and short circuits. To make the model robust, make sure the dataset includes a variety of lighting scenarios, angles, and PCB designs.

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2.2 Data Annotation:
Label each image that has been gathered with the location and kind of faults. The YOLO model must be properly trained through this annotation process in order to identify and locate flaws. For this, you can use programs such as Labelling, CVAT, or VGG Image Annotator.

2.3 Data Preprocessing:
If required, preprocess the annotated photos. Typical preparation procedures involve shrinking photos to a predetermined input size, normalizing pixel values, and enhancing the dataset using methods like flipping, rotation, and brightness correction to boost the dataset's diversity.

2.4 Model Selection and Modulation:
Use the pre-processed and annotated dataset to train a YOLO model. Depending on your particular dataset, you can fine-tune pre-trained weights orstart from scratch when training the model. As the model is being trained, keep an eye on measures like recall, loss, accuracy, and MAP (mean average precision).

2.5 Model Evaluation:
Access the trained model's ability to identify PCB flaws using a different validation set. Model accuracy and robustness can be measured using evaluation metrics such as precision, recall, F1score, and MAP.

2.6 Deployment:
Use the model in the production environment for real-time flaw detection on PCB images after it performs well enough. Incorporating the model into a quality control pipeline or an automated inspection system inside the production process may be necessary to achieve this.

2.7 Iterative Improvement:
Require the deployed system to provide feedback on a regular basis and track its effectiveness in identifying PCB faults. Continue to iterate on the model to increase its accuracy and efficiency by adding more data, enhancing the training procedure, and optimizing hyper parameters.

2.8 Maintenance and Monitoring:
Updating the model with fresh data on a regular basis and retraining it to adjust to modifications in the manufacturing process or the kinds of faults found are two important maintenance and monitoring tasks. Provide means for evaluating model performance over time to identify drift or degradation and take appropriate corrective action.
After all these steps we need to report the output of what accuracy our model has detected the defect in PCB'S.

- **Create Reports:** Gather comprehensive reports of identified flaws, including their kinds and locations.
- **User Interface:** For additional analysis and decision-making, present the findings using an intuitive user interface.

Our model performs these steps in order to detect the defects in PCB's and gives us the output of what type of defect is present in PCBs with the good accuracy.

III. RESULTS

The model we have designed performs all the methodologies in proper manner and accurately predicts the type of defects that is present in the given PCB's. Here is the following output that we have achieved through our project.
First let us see the types of defects that we have identified:

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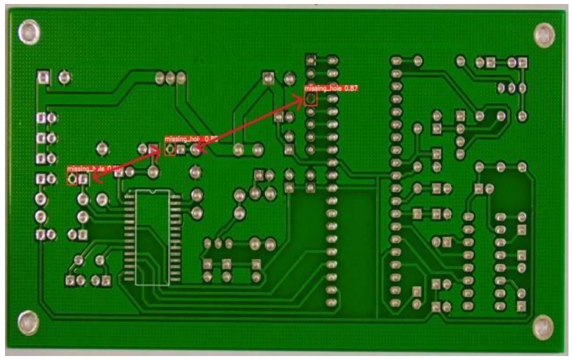
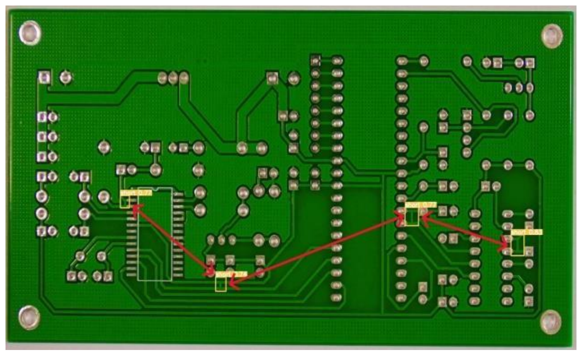
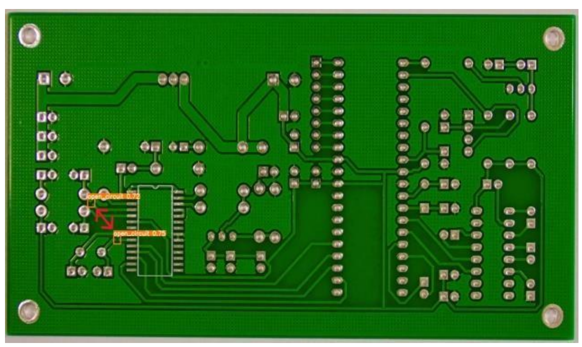
3.1 Missing Hole:



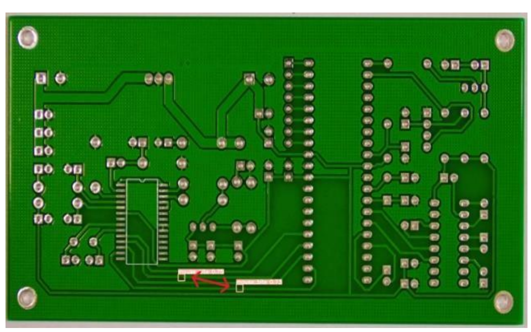
3.2 Short Circuit:



3.3 Open Circuit:



3.4 Mouse Bite:



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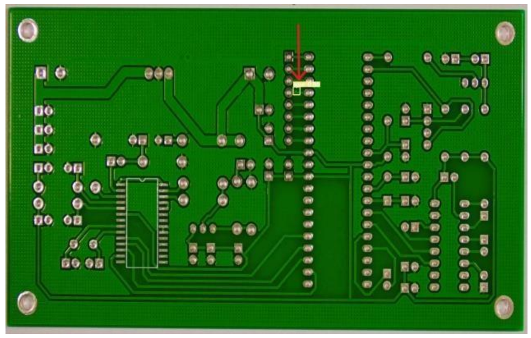
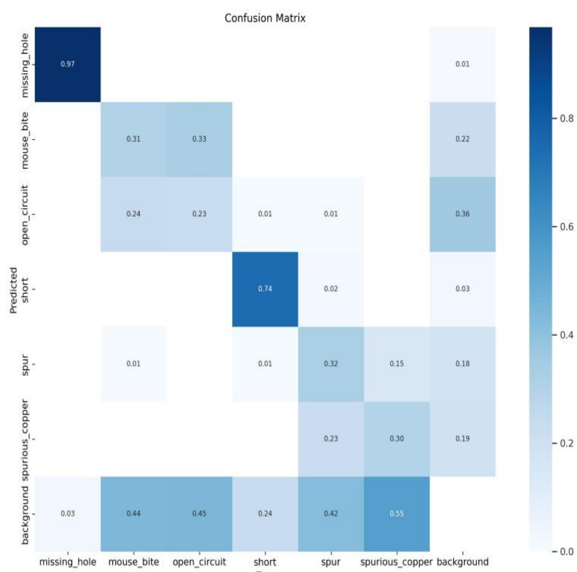
3.4 Spur:



These are the following findings of the different types of defects present in the PCB'S. Now let us see the confusion matrix which indicates the accuracy of the defect findings in PCB.

3.5 Confusion Matrix:

By these comparisons the actual and expected classifications, the confusion matrix serves as a useful tool for assessing a classification model's performance. The provided confusion matrix for the PCB flaw detection system is explained in full below:



Components of the confusion matrix:

Axes:

- **True Labels (Actual Classes):** Axes The real defect classes in the dataset are shown on the y-axis.
- **Predicted Labels:** The accurate YOLO v5 model's predictions for the classes are shown on the x-axis.

Important Cells and How to Interpret Them:

- **True Positives or Diagonal Cells:** These cells show accurate predictions when the expected label coincides with the actual label. They are arranged from top-left and they arranged from bottom-right.
- **Missing hole to missing hole:** 0.97, which indicates that 97% of real "missing hole" problems were being correctly classified by our model 74% of real "short" problems were correctly classified as such, with a short-to-short ratio of 0.74.

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- **Off-Diagonal Cells (Errors):** These cells show inaccurate predictions in which the label that is predicted does not correspond to the actual label. 1 percent of true "mouse bite" problems were mistakenly categorized as "missing holes" (mouse bite to the missing hole probability was 0.01) 44% of true "background" instances were mistakenly classified as "mouse bite," as indicated by the background to mouse bite ratio of 0.44
- **Elevated Error Rates:** 36% of true "open circuit" problems were mistakenly labelled as "spurious copper," according to the open circuit to spurious copper ratio is found to be 0.36 in matrix. 45% of real "background" occurrences were mistakenly classified as "open circuit" (background to open circuit: 0.45).

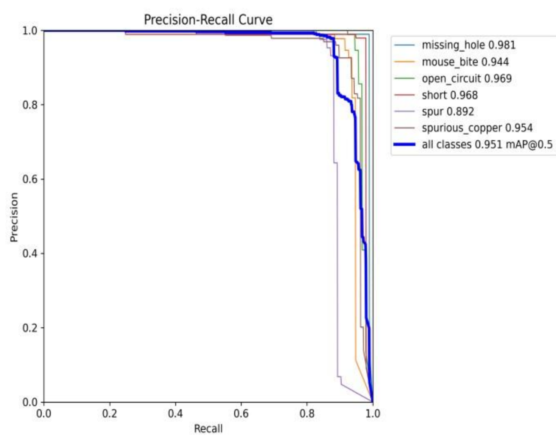
Overall Insights:

Elevated Precision for Missing Holes and

- **Shorts:** The diagonal's high values (0.97 and 0.74, respectively) demonstrate the model's exceptional performance in identifying the "missing hole".
- **Confusing Similar Defects:** It is apparent that "mouse bite" and other classes like "open circuit" and "spurious copper" are confused with one another.
  Examples of "background" that are frequently incorrectly identified as defect classes-in particular, "mouse bite" and "open circuit"-indicate that the model may have trouble telling faults apart from background noise.
- **Misclassifications:** 'Background' is categorized as 'open circuit' (0.45) and 'spur' is classified as 'open circuit' (0.32), two examples of cells with quite high values for inaccurate classifications that point to areas where the model needs to be improved.

These are the detailed explanations about the confusion matrix that we have obtained through our project.

Precision-Recall Curve:



This is called the P-R curve where, **X-axis** represents recall of the classifier.
Y-axis represents precision of the classifier.
Each curve in the graph represents the relationship between Precision and Recall.
Missing hole has a P-R curve with average precision (AP) 0.981.
Mouse bite has a P-R curve with AP 0.944.
Open circuit has a P-R curve with AP 0.969. **Short circuit** has a P-R curve with AP 0.968.
Spur has a P-R curve with AP 0.951.

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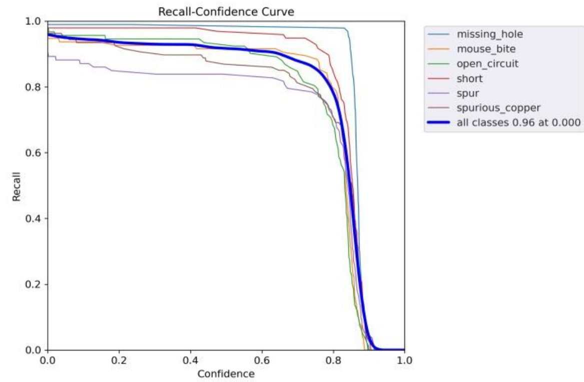
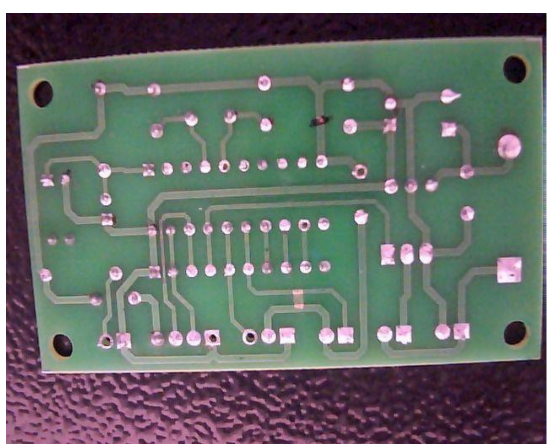
R-Curve:



X-axis represents the confidence threshold for classifying a positive instance. It has a range from 0-1.
Y-axis represents the recall of the classifier. Higher recall means false negatives.
Each curve represents the relationship between recall and the confidence threshold for a specific defect class.
Missing hole: The recall-confidence curve for the missing hole defect, which reaches 0.96 recall at a confidence level of 0.0 and retains strong recall over a variety of confidence thresholds. **Mouse bite:**The memory-confidence curve for the mouse bite defect, which gradually decreases at increasing confidence thresholds while still having a high recall.
Open circuit: The graph recall-confidence curve corresponding to the open circuit fault, displaying a comparable strong recall tendency.
Short: The memory-confidence curve for the short defect, which shows a discernible decline in recollection with increasing confidence but yet retains a high recall.
Spur: The spur defect's recall-confidence curve, which shows a lower recall than other classes especially as the confidence threshold rises.
In addition to this, as we had the main goal to implement the project even in the real time processing. So, we took a PCB which had a missing hole in it.
After that the PCB image was captured by using a webcam where we wrote a separate code for the working of the webcam, it captures the image of PCB then processes it and finally gave the output by identifying the missing hole in the given PCB. Here are the following images of the real time processing:

Before:



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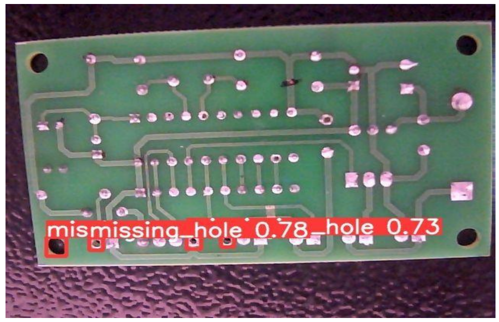
After:



Here we can see that our model was successful in identifying one of the defects of PCB i.e. missing hole.

IV. FUTURE RECOMMENDATION

- **Improved Efficiency and Accuracy:** As deep learning models, including transformer models and convolutional neural networks (CNNs), continue to advance, their ability to identify even the tiniest flaws can become more accurate. Improved algorithms can decrease false negatives and positives, increasing overall dependability.
- **Internet of Things (IoT) and Industry 4.0 framework integration:** By integrating PCB defect detection systems with these frameworks, smooth data transfer between various manufacturing stages can be facilitated. Smarter manufacturing systems with predictive maintenance and improved quality control may result from this combination.
- **Explainable AI:** Creating models with this feature can assist technicians in comprehending the reason behind a specific defect's detection. This can increase confidence in the system and offer information for further streamlining the production process.
- **Cloud-based Solutions:** Centralized data analysis, remote monitoring, and scalability can all be made possible by putting cloud-based defect detection solutions in place. For manufacturers with several production locations, this can be especially helpful.
- **Integration with Computer-Aided Design (CAD) Tools:** Computer-aided design (CAD) tools are utilized in PCB design, and deep learning-based defect detection systems can incorporate with them.

Through design optimization and reduced production failures, this can aid in spotting possible flaws early on in the process.

These are some of the future recommendations of our project that we can implement in the future.

V. CONCLUSION

The substantial potential of contemporary AI approaches in quality control procedures within the electronics manufacturing industry is demonstrated by our effort on PCB flaw identification utilizing the YOLO deep learning model. Defects on printed circuit boards (PCBs) can be easily identified and classified using the YOLO (You Only Look Once) model, which is well-known for its quickness and precision in object identification tasks.

Our study resulted in the creation of a solid dataset that included pictures of PCBs with different kinds of flaws. To make sure the YOLO model could appropriately learn and discern between various defect kinds, this dataset was painstakingly tagged. After the model was trained, a thorough testing process revealed that it could accurately identify flaws and recall them at a high rate; hence lowering the likelihood those faulty products would be sold.

This paper's primary contribution is the lightweight model it proposes, which can evaluate object types fast and precisely without requiring the use of the conventional massive migration model. A number of techniques were employed to enhance the model's training effect in addition to certain modifications made to the model's architecture to enable the lightweight model to achieve more accuracy with fewer parameters.

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REFERENCES

[1]. PCB Defect Detection Using Denoising Convolutional Autoencoders Khalilian, S., Hallaj, Y., Balouchestani, A., Karshenas, H., Mohammadi, A. in The 2020 International Conference on Machine Vision and Image Processing (MVIP), held February 18–20, 2020, in Qom, Iran.

[2]. CNN-based reference comparison technique for PCB defect classification (Wei, P.; Liu, C.; Liu, M.; Gao, Y.; Liu, H.). 2018 J. Eng. 16.

[3]. Automated Visual PCB Inspection Algorithm: A Survey by P.S. Malge and R.S. Nadaf. 2014; Int. J. Eng. Res. Technol., 3. Accessible over the internet at https://www.ijert.org/a-surveyautomated-visual-pcb-inspection-algorithm (retrieved on April 15, 2020).

[4]. Malge, P.S. and Nadaf, R.S. employed mathematical morphology and image processing techniques to detect, classify, and localize PCBdefects. Int. J. Comput. Appl. 2014.

[5]. Cubuk, E.D.; Le, Q.V.; Zoph, B.; Ghiasi, G.; Cui, Y.; Srinivas, A.; Qian, R.; Lin, T.Y. For instance segmentation, basic copy-paste is a powerful data augmentation strategy. In Nashville, Tennessee, USA, June 20–25, 2021, IEEE/CVF Conference on Computer Vision and Pattern Recognition Proceedings.

[6]. Farhadi, A.; Girshick, R.; Divvala, S.; Redmon, J. Real-time, unified object detection means you only need to look once. In the proceedings of the 2016 June 27–30 IEEE Conference on Computer Vision and Pattern Recognition, held in Las Vegas, NV, USA.

[7]. SSD: Single-shot multibox detector Liu, W.; Anguelov, D.; Erhan, D.; Szegedy, C.; Reed, S.; Fu, C.Y. ; Berg, A.C. Reprinted in Proceedings of the 14th European Conference, October 11–14, 2016, Amsterdam, Netherlands.

[8]. Kumar, V.V.; Sarath, N.S.; Anoop, K.P. an examination of image processing for PCB flaw identification. J. Eng. Innov. Technol. Intern. 2015.

[9]. Automated visual assessment of surface mounted chip components Wu, H.; Feng, G.; Li, H.; Zeng, X. In the proceedings of the August 4–7, 2010, Xi'an, China, IEEE International Conference on Mechatronics and Automation.

[10]. Fischer, P.; Brox, T.; Ronneberger, O. U-net: Convolutional networks for biomedical picture segmentation. in The International Conference on Medical Image Computing and Computer-Assisted Intervention, October 5–9, 2015, Munich, Germany.

[11]. Faster r-cnn: Achieving real-time object detection with region proposal networks is the goal of Ren, He, Girshick, Sun, and S. He. 39. IEEE Trans. Pattern Anal. Mach. Intell. 2017.