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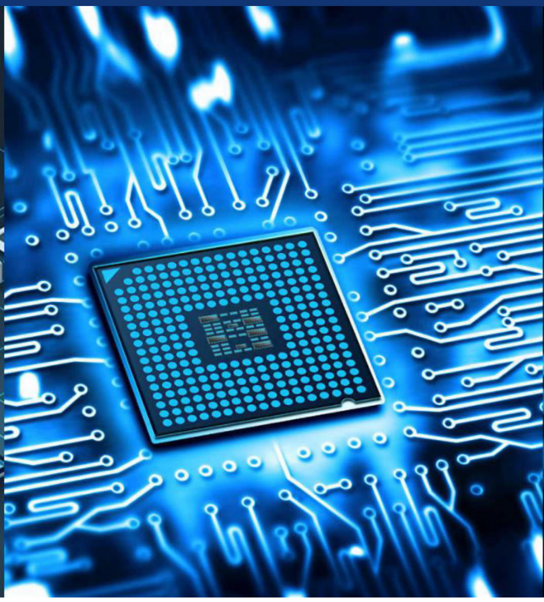


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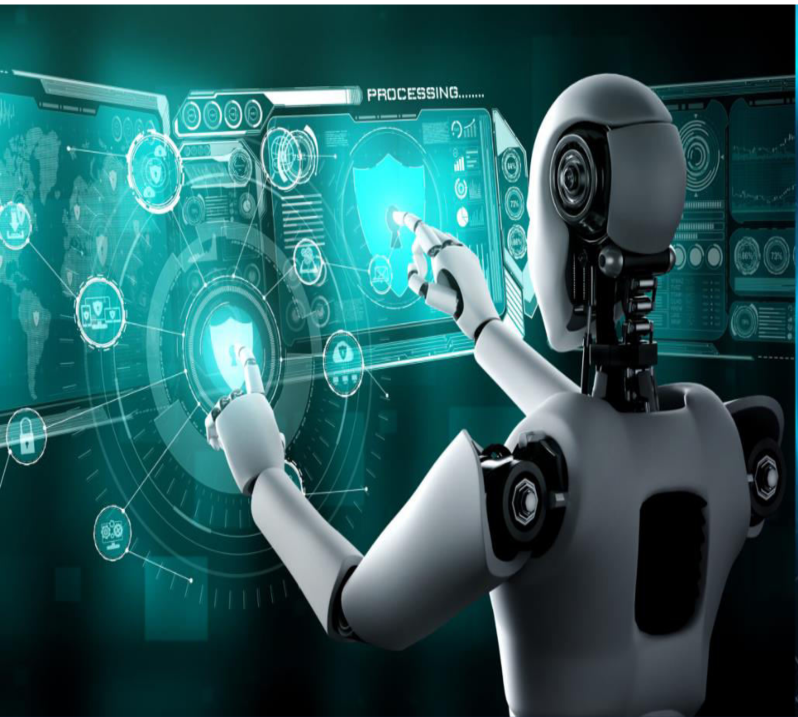

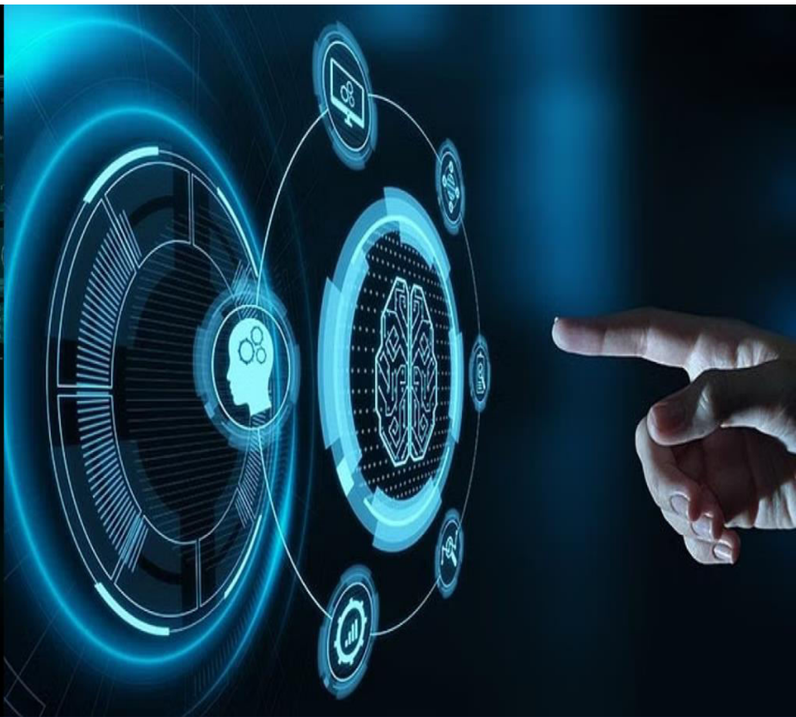

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PCB Defect Detection using Deep Learning and Synthetic Data Generation with ControlNet

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ABSTRACT: This defect detection in printed circuit boards (PCBs) is crucial to ensure reliability and functionality of the equipment used in all Industries. Based on the analysis, this paper develops a new PCB defect detector composed of Swin Transformer and synthetic data generation based on ControlNet. Lack of availability of data and expensive labeling process makes the traditional method of defect identification unproductive. To overcome these challenges, this study uses ControlNet to create relevant synthetic defect samples that enrich the dataset and enhance generalization. Experimental findings show high increase in performance from 87.5% to 93.4% in accuracy; 85.2% to 91.8% in precision and 83.6% to 91.2% in F1-score by integrating synthetic data. The proposed approach had better performance than baseline models, including CNN and YOLOv5, especially in detecting complex and rare defects. The findings of this research also serve the purpose of enhancing the reliability and efficiency of PCB inspection to reveal the effectiveness of using more sophisticated methods of data augmentation and transformer-based models in industrial problems.

KEYWORDS: PCB Defect Detection; Synthetic Data Generation; Swin Transformer; ControlNet

I. INTRODUCTION

Printed Circuit Boards (PCBs) are descriptive components that are used as substrates in today's electronics by providing interconnectivity and working as an interface into various applications such as in consumer electronics, telecommunication, automobile, and industrial uses [1]. They are used to support individual parts and enable their connection to other components in a way that will allow a device to function optimally in different conditions [1, 2]. Nevertheless, as printed circuit board (PCB) configurations grow progressively sophisticated with denser layouts and intricate circuits, defect identification in manufacturing has emerged as a significant challenge. Quality and reliability standards are critical because even minor PCB flaws can lead to device failures, reduced product lifespan, or risks in critical applications like medical devices and aerospace systems [3, 4, 5].

Traditionally, PCB inspection relied on manual examination or Automated Optical Inspection (AOI) systems. Manual inspection, requiring trained personnel and magnifying tools, is slow, laborious, and susceptible to inaccuracies, particularly in high-volume manufacturing contexts [6]. AOI systems, employing high-resolution cameras and algorithms, improved inspection speed and consistency but face limitations in handling complex PCB designs. These systems struggle to differentiate fine, overlapping patterns in dense layouts and require substantial investment in specialized equipment and expertise [7, 8].

Deep learning presents a viable approach to address these constraints. Models for instance Convolutional Neural Networks (CNNs) along with transformer-based architectures demonstrate superior performance in defect classification and object detection by directly assimilating intricate and hierarchical patterns from data [9, 10, 11]. However, these models demand extensive annotated datasets, which are costly and time-consuming to produce. Moreover, the subtlety

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and variability of PCB defects further exacerbate the challenge, leading to poor generalization in models trained on limited datasets [12].

Synthetic data generation has been proposed to mitigate these challenges. Methods including Generative Adversarial Networks (GANs) and data augmentation have enhanced model performance by creating diverse training data [13]. Despite their promise, traditional GANs often suffer from instability during training and require significant real-world data for effective results [14]. Conventional augmentation techniques, such as flipping and rotation, modify existing data but fail to generate entirely new defect types [15, 16].

In this research, we propose a novel method integrating ControlNet, a state-of-the-art image-to-image translation tool, with the Swin Transformer architecture. ControlNet enables precise simulation of specific defect types—such as soldering faults, missing components, and surface cracks—mimicking real-world conditions with high fidelity [17, 18]. These synthetic datasets are integrated with Swin Transformer's hierarchical attention mechanisms to improve defect detection accuracy and generalization [19]. The model's ability to analyze characteristics across multiple mesures allows it to handle both subtle and complex defects effectively, addressing key limitations of CNN and YOLO-based approaches [20].

This framework introduces groundbreaking advancements in PCB defect detection, bridging existing gaps in traditional and deep learning-based approaches. By addressing these challenges, this study enhances the dependability, effectiveness, and expandability of quality assurance methodologies in electronic manufacturing. Further details of the methodology and experimental validations are discussed in subsequent sections.

Research Objectives
This study aims to:
• **Revolutionize Synthetic Data Generation:** Develop a robust pipeline using ControlNet to produce highly realistic and diverse synthetic datasets, addressing the scarcity of annotated PCB defect data.
• **Achieve Superior Detection Accuracy:** Combine synthetic data with Swin Transformer's advanced hierarchical feature extraction to enhance the precision and recall of defect detection.
• **Enhance Industrial Scalability:** Design a framework capable of minimizing false positives and negatives, ensuring seamless integration into high-demand industrial workflows.
• **Reduce Annotation Effort:** Leverage synthetic data to significantly reduce the dependency on manual labeling, saving time and resources.
• **Expand Defect Detection Capabilities:** Demonstrate the Swin Transformer's ability to detect both micro-scale and macro-scale defects, offering a comprehensive solution for complex PCB designs.

This framework introduces groundbreaking advancements in PCB defect detection, bridging existing gaps in traditional and deep learning-based approaches. By addressing these challenges, this study contributes to the dependability, efficiency, and scalability of quality assurance processes in electronic manufacturing.

This manuscript is organized in the following way: Section 2, presents the related work with regards to PCB defect detection and synthetic data generation. Section 3 highlights the research method of the proposed model, as well as the process of generating synthetic data. Section 4 explains details of the experiments including the datasets used, tools and the training regime. The findings as well as the improvements made through the incorporation of synthetic data are outlined in section 5 of provided paper. Last of all, Section 6 provides a conclusion to the study and a discussion on the future works, particularly on the future opportunities of synthetic data as well as transformer architectures for PCB defect detection. Thus, this research fills the gap of the current the current landscape both state-of-the-art and practical applications through providing a solution to the limitations of conventional defect detection methods and through introducing the potential of synthetic data application to the depth of the deep learning architectures used in the PCB inspection. This study has implications in enhancing efficiency, reliability, and cost of defect detection in the electronic manufacturing firm to support quality assurance.

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II. RELATED WORK

Defect inspection of Printed Circuit Boards (PCBs) has been another contribution of research endeavors in electronics manufacturing since its aim is to increase the quality as well as functionality of manufacturing operations. For several years, these improvements have been observed, especially when machine learning and deep learning approaches were incorporated. This section gives detailed analysis of previous research work done with reference to the historical development of defect detection processes, issues on synthetic data generation, and capabilities of the new deep learning architectures in addressing the challenges.

Traditional Approaches to PCB Defect Detection

Fung et al. [16] utilized selective feature attention and pixel shuffle pyramid techniques to enhance defect detection in PCBs, addressing challenges related to small defect localization. Yao et al. [17] introduced self-supervised learning approaches for PCB defect detection, focusing on local image patches to improve model training efficiency. Gao et al. [18] proposed a compressed target detection model aimed at improving computational efficiency in PCB surface defect detection. Jiang et al. [21] integrated multi-scale and attention mechanisms to improve PCB defect detection accuracy in complex layouts. Ong [36] introduces a real-time PCB inspection approach driven by CAD data, utilizing dynamic alignment techniques to streamline traditional defect detection workflows. Rasika et al. [37] employ image processing techniques for PCB defect detection, focusing on identifying and quantifying anomalies to ensure robust quality control.

Collectively, these approaches demonstrate the evolution from traditional AOI systems to more efficient, scalable, and precise solutions for high-density PCB layouts.

Advancements in Deep Learning Architectures

Zhang et al. [25] present a lightweight one-stage defect detection framework for small objects, employing a dual attention mechanism and PAFPN to boost feature representation and achieve high detection accuracy in defect scenarios. Legon et al. [22] utilize deep learning methods for the detection and classification of PCB defects, demonstrating improved inspection accuracy and robustness in industrial PCB applications. Yao et al. [26] proposed a self-supervised learning framework tailored for PCB defect detection, which significantly reduced the dependency on labeled datasets. Kim et al. [24] propose a multiscale feature pyramid network architecture to effectively capture small objects by integrating refined feature representations across multiple scales, leading to improved detection performance in challenging scenarios. Wan et al. [27] introduced lightweight convolutional neural networks optimized for real-time detection in manufacturing environments, offering a balance between accuracy and computational efficiency. Jiang et al. [28] emphasized the integration of multi-scale attention mechanisms to enhance feature extraction capabilities, particularly for detecting intricate defect patterns in PCBs. Ma et al. [31] introduce an automated approach for detecting voids in high-resolution X-ray PCB images, leveraging a deep segmentation neural network to enhance detection accuracy and efficiency. Lim et al. [33] propose a deep context learning-based PCB defect detection approach integrated with an anomalous trend alarming system, facilitating early warning and more accurate fault analysis in industrial applications. You [34] presents a PCB defect detection framework leveraging Generative Adversarial Networks to generate and learn from synthetic samples, aiming to improve detection accuracy in PCB inspection tasks. Ma et al. [35] propose a hierarchical attention detector for bearing surface defect detection, effectively leveraging multi-granularity attention and robust feature extraction to enhance defect identification accuracy. Lu et al. [38] propose an anchor-free defect detection approach for complex backgrounds, leveraging pixelwise adaptive multiscale feature fusion to effectively enhance detection performance and handle various defect scales. Hoang and Tran [40] present a training strategy for noise-robust deep neural networks targeting socket defect detection, emphasizing robust learning under noisy conditions to enhance detection accuracy. These approaches underscore the transformative role of deep learning in overcoming limitations posed by traditional methods.

Synthetic Data Generation for PCB Defect Detection

Bougaham et al. [23] utilized generative adversarial networks (GANs) to create synthetic defect samples, addressing the challenge of limited annotated datasets in PCB inspection. Wang et al. [29] highlighted the effectiveness of GAN-based data augmentation in improving model generalization, particularly for rare defect types. Yang et al. [30] integrated synthetic datasets into improved YOLOv8 architectures, demonstrating enhanced accuracy and robustness in defect detection tasks. These advancements illustrate the critical role of synthetic data in bridging the gap between real-world complexities and model training requirements.

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Comparative Studies on Baseline Models

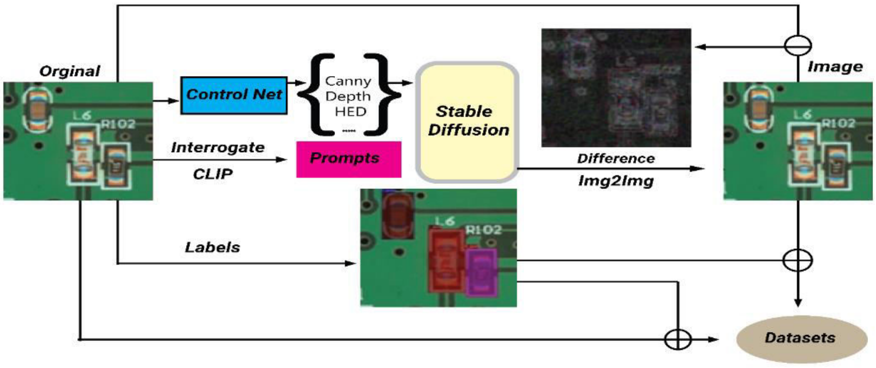

Fig. 1. Automatic Sample Generation Method

This figure illustrates the synthetic data generation pipeline, showcasing the integration of ControlNet and Stable Diffusion. It demonstrates how real-world cues and constraints are utilized to simulate diverse PCB defect conditions, contributing to enhanced dataset diversity and model robustness.

To address the scarcity of annotated datasets, synthetic data generation has emerged as a promising solution. Techniques such as Generative Adversarial Networks (GANs) and data augmentation have been employed to create diverse and realistic training datasets [26]. While GANs have been instrumental in generating synthetic defect images, they often suffer from training instability and require substantial real-world data for optimal performance [27].

A more recent innovation, ControlNet, offers a controlled approach to synthetic data generation. Unlike traditional GANs, ControlNet enables precise simulation of specific defect conditions, such as soldering faults and surface cracks, by leveraging real-world constraints and cues. This targeted generation method significantly enhances dataset diversity and realism, improving model robustness and generalization capabilities [28, 29].

Numerous studies have compared the performance of baseline models for PCB defect detection. Kong et al. [26] introduced self-supervised learning frameworks for PCB defect detection, significantly reducing dependency on labeled datasets while maintaining high accuracy. Xu et al. [27] proposed lightweight convolutional neural networks optimized for real-time defect detection, demonstrating a balance between speed and precision. Jiang et al. [28] emphasized the integration of multi-scale attention mechanisms to improve feature extraction, particularly for intricate defect patterns in PCB layouts.

In contrast, transformer-based models such as Swin Transformer, highlighted by Ling et al. [32], showcased superior accuracy, precision, and recall. These models leverage hierarchical attention mechanisms to capture multi-scale features, addressing limitations found in traditional CNNs and YOLO models. Furthermore, Wang et al. [39] demonstrated that incorporating synthetic datasets significantly enhances these models' robustness and generalization capabilities, making them highly suitable for industrial defect detection scenarios.

Research Gap

Although PCB defect detection has improved tremendously over the years, the following issues persist. It can be seen that the classical techniques of automated optical inspection AOI, as well as visual inspection, are no longer enough to provide the necessary level of quality control for electronics production nowadays. Conventionally used deep learning models, including CNNs and transformers, have applied but suffer from the lack of annotated samples and the challenges of PCB defects. Synthetic data generation specifically using advanced tool like ControlNet can address these challenges effectively and provide diversified realistic samples of defects. This research intends to extend from the prior knowledge by adopting ControlNet synthesized data together with Swin Transformer for improved defect inspection. Therefore, based on the above-said limitations of traditional techniques and exploring the potential of

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superior deep learning models, this research intends to add further to the advancement of PCB inspection technologies toward enhanced reliability and effectiveness of electrical products in the electronics sector.

III. METHODOLOGY

To perform synthetic data generation, this work employs the ControlNet architecture, while for the multi-scale defect detection, the Swin Transformer is utilized. Swin Transformer incorporates hierarchical attention mechanisms, while ControlNet synthesizes synthetic PCB defect samples as their method to expand the training sample collection. The model is intended to integrate these components to enhance the precision of the defect detection and generalization in addition to addressing the poor data availability.

The deep learning model structure can be explained in the following way.

$$M(x) = f_{swin}(g_{ControlNet}(x)) \qquad \text{eq. (1)}$$

Where M(x) is the output, the defect classification, from the model for the input x, f_{swin} is the hierarchical processing of Swin Transformer while $g_{ControlNet}$ is the generation of synthetic image from the ControlNet. This structure allows for fine-grained defect detection across multiple scales, leveraging both real and synthetic datasets.

ControlNet is used to produce synthetic PCB defect cases. Let $D_{synthetic}$ represent the set of synthetic images created by ControlNet. The generated data increases dataset diversity, filling gaps where real-world samples are sparse.

The core process involves mapping defect characteristics (such as defect type, location, and size) to an output image, defined as:

$$D_{synthetic} = G_{ControlNet}(z, c) \qquad \text{eq. (2)}$$

Where $G_{ControlNet}$ is the generator function, z represents the latent space variables (random noise), and c denotes the conditional information such as defect type. This enables ControlNet to generate highly controlled and targeted defects. By augmenting the real-world dataset D_{real} with $D_{synthetic}$, the final dataset used for training is

$$D_{total} = D_{real} \cup D_{synthetic} \qquad \text{eq. (3)}$$

This combined dataset helps ensure that the model is exposed to both common and rare defects, enhancing generalization.

Deep Learning Model

The Swin Transformer serves as the backbone for defect detection as highlighted in [11]. Swin Transformer operates on shifted window-based self-attention mechanisms, it aims to encompass both universal and specific contextual insights. The Swin Transformer can be mathematically represented as follows.

$$y_i = SwinLayer(x_i) = W_{shifted} \times x_i \qquad \text{eq. (4)}$$

Where $W_{shifted}$ represents the shifted attention window applied to input x_i, and y_i is the output of the Swin layer. Multiple Swin layers are stacked to capture multi-scale features, making it highly effective for detecting defects of varying sizes. The hierarchical nature of the architecture ensures that both microscopic and macroscopic defects are identified, overcoming the limitations of conventional convolutional approaches [Figure 2].

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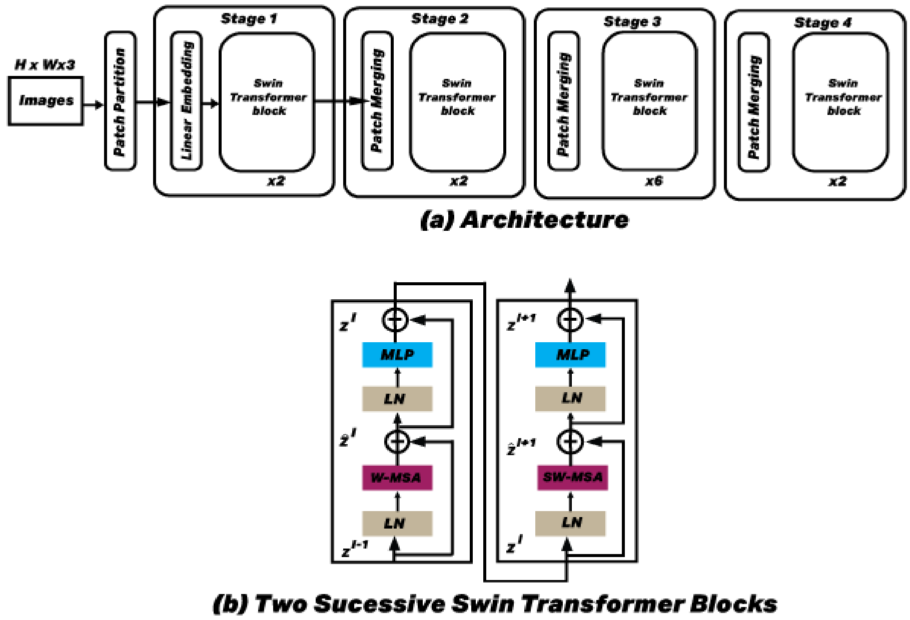

Fig. 2. Two Stage SWIN Transformer Block

The training process involves the following key stages.

- **Data Preprocessing:** The input data (both real and synthetic) is preprocessed through resizing, normalization, and augmentation. Let D'_{total} represent the preprocessed dataset.

$$D'_{total} = Preprocess(D_{total}) \qquad \text{eq. (5)}$$

- **Loss Function:** The model is trained using a cross-entropy loss function L, which measures the difference between the predicted defect class $\hat{y}$ and the true label y.

$$L = \sum_{i=1}^{N} y_i log\ (\hat{y}_i) \qquad \text{eq. (6)}$$

Where N denotes the number of samples is, y_i is the true label, and $\hat{y}_i$is the predicted probability for class i.

- **Optimization:** The model is optimized using the Adam optimizer, with the following update rule for the parameters θ.

$$\theta_{t+1} = \theta_t - \eta \nabla_{\theta_t} L \qquad \text{eq. (7)}$$

Where η denotes the learning rate, and $\nabla_{\theta_t} L$ is the gradient of the loss with respect to the parameters.

- **Training with Synthetic Data:** The model is trained using a combination of real and synthetic data, represented as D'_{total} ensuring that the network is exposed to a wide variety of defect types, thus improving generalization.

Evaluation Metrics

The model's performance is evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score.

- **Accuracy:** The ratio of correctly predicted defect classes to the total number of predictions, expressed as:

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$$Accuracy = \frac{\sum_{i=1}^{N} 1(\hat{y}_i - y_i)}{N} \qquad \text{eq. (8)}$$

Where 1 is the indicator function that returns 1 if the prediction $\hat{y}_i$ matches the true label y_i, and 0 otherwise.

- **Precision:** The ratio of true positives TP to the sum of true positives and false positives FP.

$$Precision = \frac{TP}{TP + FP} \qquad \text{eq. (9)}$$

- **Recall:** The ratio of true positives to the sum of true positives and false negatives FN:
-

$$Recall = \frac{TP}{TP + FN} \qquad \text{eq. (10)}$$

- **F1-Score:** The harmonic means of precision and recall, calculated as:

$$F1 = 2.\frac{Precision.Recall}{Precision + Recall} \qquad \text{eq. (11)}$$

These metrics are computed over both real and synthetic data to assess the model's ability to generalize and detect rare defects.

IV. EXPERIMENTAL SETUP

The experiment uses two types of datasets, a real-world PCB image dataset and a synthetic dataset produced using ControlNet. The real-world dataset [Figure 3] consists of annotated images of PCBs acquired from an industrial setting that shows different defects such as missing components, soldering problems and misalignment. Initially, this dataset was very limited in scope, particularly for rare and complex defect types. As per [12, 13], this scarcity of diverse defects often results in suboptimal performance of deep learning models owing to lack of data for training and validation.

To address this limitation, we generated synthetic data using ControlNet, a powerful image-to-image transformation tool for adding specific, targeted defect features into existing PCB images. As highlighted by authors in [14], ControlNet simulates realistic defect patterns by taking input of defect prompts and existing image features. The synthetic dataset substantially enhances the training dataset by incorporating subtle and rare defects, while the application of inverse color maps, depth features, and Canny edge detection techniques, as demonstrated in [7, 15], contributes to defect diversity and is further complemented by ControlNet's augmentation of model generalization capabilities. We then combine the real-world and synthetic datasets, creating a robust dataset having many types and configurations of defects. In addition to increasing data diversity, this approach reduces dependence on extensive manual labeling, as synthetic defects follow the annotations of real samples to streamline the annotation process.

The experiments used a robust setup for training deep learning models and synthetic data generation. Python 3.8 was used for programming while the core deep learning framework was TensorFlow. As TensorFlow can handle large datasets, it was used in order to train the model having support for deep learning applications. ControlNet was used to manipulate images in the Stable Diffusion framework to generate synthetic data that adds realistic defects to PCB images. Real and synthetic datasets were annotated efficiently using the LabelMe tool to ensure consistency in the labeling of both kinds of real and synthetic datasets.

For training the complex Swin Transformer based model and to accommodate large batch size the NVIDIA RTX 3080 GPU with 12 GB of VRAM was used. This GPU configuration was very useful in cutting down the training time and learning from high dimensionally datasets. We also applied the AdamW optimizer to train the model; it allows the model to learn the rate which is effective to converge This made it easy to implement the experiments and to enhance the proper data processing, model training, and generation of synthetic data.

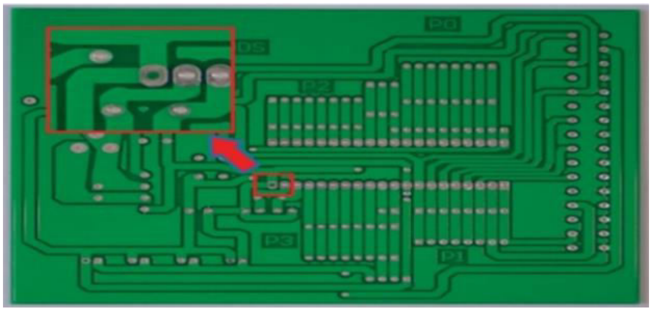

Fig. 3. A sample of defected PCB (Missing hole)

Model Training

The parameters of the PCB defect detection model which includes hyperparameters, loss functions and training period were trained well in order to have the best performance of the model. Key hyperparameters included a batch size of $B = 2$ and an initial learning rate $\eta = 0.0001$, optimized using the AdamW optimizer. AdamW was chosen for its ability to adjust the learning rate for each parameter individually, updating parameters θ according to

$$\theta_{t+1} = \theta_t - \eta . \frac{m_t}{\sqrt{v_t} + \varepsilon} - \lambda\theta_t \quad \text{eq. (12)}$$

where m_t and v_t are the estimates of the first and second moments of the gradients, and λ represents the weight decay factor, helping to prevent overfitting and enhance convergence stability in complex models like the Swin Transformer. For the classification of defect types, the model was trained using cross-entropy loss L_{CE}, which measures the discrepancy between the true labels y and the predicted probabilities $\hat{y}$. This is defined as:

$$L_{CE} = -\sum_{c=1}^{C} y_c \log(\hat{y}_c) \quad \text{eq. (13)}$$

where C is the number of classes. For models with bounding box predictions, smooth L1 loss $L_{SmoothL1}$ was incorporated, which balances the localization error by using a L1 loss for small errors and a L2 loss for larger errors.

$$L_{SmoothL1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise} \end{cases} \quad \text{eq. (14)}$$

This combination of cross-entropy and smooth L_1 loss ensured a balanced optimization for both accurate defect classification and precise localization.

The model was trained over 200 epochs, with a learning rate warm-up during the initial epochs, allowing the rate to ramp up linearly to η to stabilize training, followed by gradual decay to fine-tune the model. This decay followed a cosine annealing schedule, refining the model as it approached convergence. With an NVIDIA RTX 3080 GPU (12GB VRAM), each training session was 1.5 hours, allowing us to process both the real and synthetic data from ControlNet quickly. Therefore, the model was able to generalize well across different defect types, and hence achieve high accuracy in PCB defect detection.

V. RESULTS AND DISCUSSION

The performance of the proposed model improved significantly with the inclusion of synthetic data generated with ControlNet. Table 1 shows how using both real and synthetic data improved all key metrics such as accuracy, precision, recall, and F1 score.

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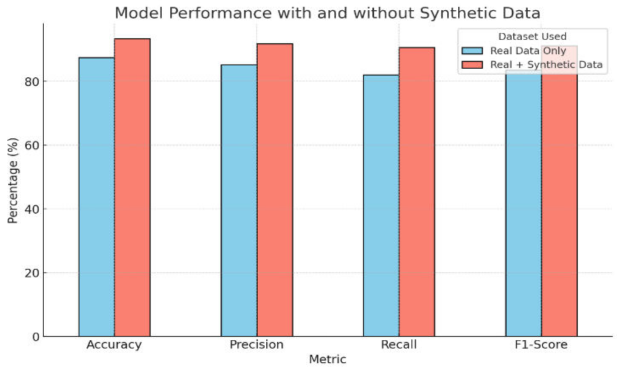
Table 1: Model Performance Metrics

Metric	Real Data Only	Real + Synthetic Data
Accuracy	87.5	93.4
Precision	85.2	91.8
Recall	82.1	90.7
F1-Score	83.6	91.2

As one can observe in Figure 4, the model trained using synthetic data received higher scores on each all the metrics. Therefore, this improvement shows that the model could detect defects with higher precision thus reducing on the false positive and increasing on the true positive values.



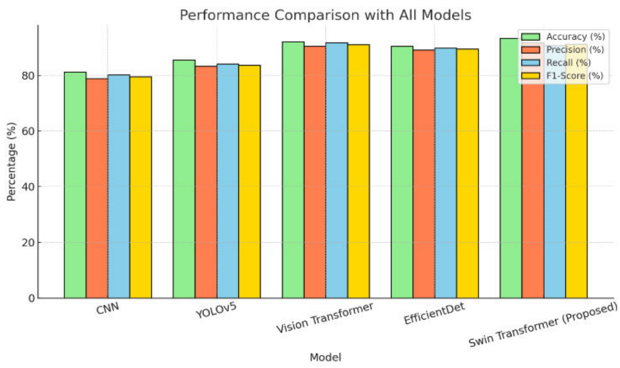


Fig. 4. Model Performance with and without Synthetic Data **Fig. 5.** Performance Comparison with Baseline Models

A comparison with the baseline models will also demonstrate the performance of the Swin Transformer model with synthetic data. As demonstrated in Table 2, the proposed model achieved significantly higher performance on all metrics relative to these baselines.

Table 2: Baseline Model Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN (Baseline)	81.2	78.9	80.2	79.5
YOLOv5	85.5	83.3	84.1	83.7
Vision Transformer	92.1	90.4	91.7	91.0
EfficientDet	90.5	89.1	89.8	89.4
Swin Transformer (Proposed)	93.4	91.8	90.7	91.2

When comparing the baseline models in the graph in Figure 5, the Swin Transformer with synthetic data presented better performance compared to the CNN, YOLOv5, Vision Transformer, and EfficientDet in terms of accuracy and F1-score. This points to the fact that the hierarchical attention mechanism of the Swin Transformer when combined with diverse synthetic data leads to a significant enhancement in the defect detection ability.

The application of synthesized data created with ControlNet proved beneficial in identifying hard-to-find and intricate problems. The use of synthetic data to teach the model rare and subtle defects, which are not easily identifiable in real datasets, therefore, increased the model's recall and precision. This enhancement is necessary for industrial applications as it minimizes the time gaps that are common in erroneous detection while maximizing the defect coverage. The outcomes confirm that the use of synthetic data enriches the dataset and increases model robustness when facing an insufficient number of training samples, thus enhancing reliable and accurate identification of PCB defects.

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Model Training Patterns Analysis

The training patterns highlight a noticeable difference in the accuracy and loss profiles across the training epochs in models that are trained on real data against models trained on a combination of real and synthetically generated data.

1. **Training Accuracy**

- With only real data the trained model shows constant increase in accuracy up to about 88% after about 150 epochs as depicted in Figure 3. The reduced convergence rate indicates that the model is less exposed to different forms of defects, thus taking longer to make generalizations.
- In contrast, the model trained with synthetic data achieves faster convergence, reaching about 90% accuracy by epoch 100 and plateauing near 93% by epoch 150 (Figure 6). Diversity of the synthetic data allowed the model to generalize more quickly during the learning process and achieve higher peak accuracy.

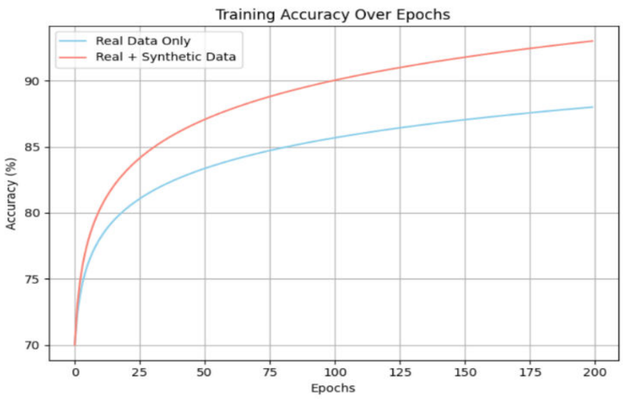

Fig. 6. Training Accuracy Over Epochs

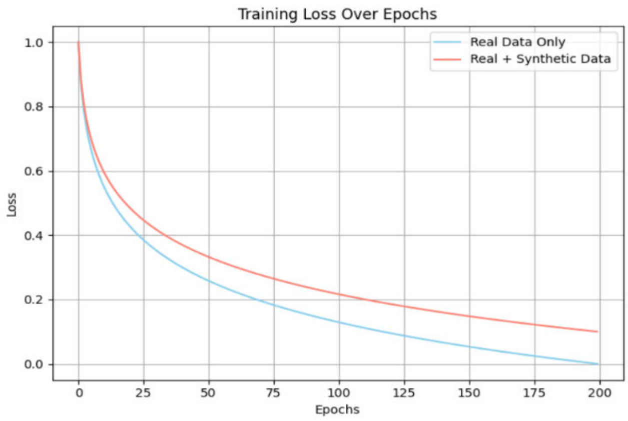

Fig. 7. Training Loss Over Epochs

2. **Training Loss**

- The loss pattern in the figure follows a clear trend. Specifically, the loss of the model trained solely on real data decreases more rapidly and stabilizes at a lower level compared to the model trained with both real and synthetic data.
- Using synthetic data slows down the reduction in loss, as the loss remains higher throughout the training process. This suggests that the inclusion of synthetic data introduces additional complexity, possibly due to the representation of diverse and challenging defect scenarios.

In Figure 7, these patterns indicate that while synthetic data may hinder the speed of training and delay convergence, it could provide the model with exposure to a broader range of defect cases, potentially enhancing its generalization capabilities.

VI. CONCLUSION AND FUTURE WORK

This paper demonstrates a new method of PCB defect detection through the Swin Transformer model and synthetic images created by ControlNet. Thus, the issues related to the conventional methods of defect detection which are based on the limited dataset real life scenarios and poor generalization capabilities in the deep learning models were addressed. To enrich the dataset and allow the model to recognize rare and complex defect patterns, the proposed method generated targeted synthetic defect samples. Our experimental results showed significant gains in accuracy, precision, recall and F1 score, as the accuracy rose from 87.5% to 93.4% with the addition of synthetic data. In comparison to baseline models CNN and YOLOv5, the proposed model demonstrated superior performance, highlighting the effectiveness of combining ControlNet produced data with the Swin Transformer for PCB defect detection.

Some enhancements can be made in the future to further strengthen this research. Second, the model can be deployed for real time PCB defect detection in manufacturing to gain practical insights and identify where further refinement may be needed. Moreover, to fill any remaining gaps of defect diversity, future work could include advanced data

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augmentation techniques with transformer-based models such as ViTs or DALL E for even more realistic defect simulation. A second promising direction is to use generative models (i.e., Diffusion Models, GANs with PCB focused prompts) to expand the synthetic data generation scope to generate diverse but more precise defect types. Additionally, self-supervised learning approaches could be investigated to decrease dependence on annotated datasets and the model could learn from images that are unlabeled. With the advancements in synthetic data and transformer architectures, these improvements have the potential to increase the reliability and efficiency in PCB defect detection during electronic manufacturing.

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