Integration Artificial Intelligence with Conventional X-Ray Inspection for Improved Solder Void Detection in SSDC SiC Modules

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***Abstract*—In the context of electric vehicles (EVs), the demand for advanced power modules has grown significantly. Single Side Direct Cooling Silicon Carbide (SSDC SiC) is a key platform in the Onsemi VE-Trac™ Family, designed for EV-traction inverters. This platform features advanced cooling and semiconductor technologies to ensure high performance and reliability. However, one of the critical challenges in manufacturing SSDC SiC modules is the detection of solder voids. Solder voids can significantly compromise the reliability and performance of power modules by reducing the effectiveness of heat dissipation and leading to potential failures. Conventional inspection methods relying solely on X-ray machines are often time-consuming and prone to human error, highlighting the need for a more efficient and accurate approach. The primary aim of this research is to develop an Artificial Intelligence (AI) based system to serve as a secondary validation layer for void detection in SSDC SiC modules. This system works in conjunction with X-ray machines, providing independent and accurate results for solder void inspections. This study leverages semantic segmentation techniques by using deep learning approach which is Convolutional Neural Networks (CNN), specifically U-Net, to classify void pixels from the background in X-ray images. The system processes output images from X-ray machines, differentiating void pixels from the background with high precision. Preliminary results indicate that the AI-based system can accurately classify solder voids, significantly reducing false positives and negatives compared to conventional inspection methods. The integration of this system with existing X-ray inspection processes promises enhanced detection, contributing to the improved solder void detection of SSDC SiC modules.**

***Keywords*—CNN, Deep Learning, SSDC, SiC, X-ray, U-Net**

I. INTRODUCTION

Single Side Direct Cooling (SSDC) Silicon Carbide (SiC) is a component of the Onsemi VE-Trac™ Family of power modules, which is intended especially for traction inverters used in hybrid vehicles (HEVs) and electric vehicles (EVs). To improve thermal performance and reliability, the module incorporates a single, semi-900V Silicon Carbide Metal-Oxide-Semiconductor-Field-Effect Transistor (SiC MOSFET), that is attached using silver sintering technique and grouped in a 6-pack arrangement [1]. The power module for signal terminals has a new type of press-fit pins that allow for simpler construction and dependable connections. Additionally, it incorporates an optimized pin-fin heatsink into the baseplate to give the circuit strong, reliable mechanical support and a direct thermal path for heat dissipation [2]. Fig. 1 shows SSDC module structure which Die Bond Copper (DBC) is in orange color.

Artificial Intelligence (AI) is revolutionizing semiconductor manufacturing by enhancing efficiency and reliability [3]. With the growing demand for advanced power modules in the EV market, ensuring the reliability of SSDC SiC modules is crucial. One major challenge is the detection of solder voids between DBC to heatsink as shown in Fig. 1, which can impair module performance by reducing heat dissipation [4]. Conventional X-ray inspection techniques take a lot of time, effort, and are prone to mistakes, which can result in problems like over- or under-detection [5-6]. As a secondary validation layer for void identification in SSDC SiC modules, an AI-based approach is suggested as a way to enhance this. Using semantic segmentation with Convolutional Neural Networks (CNN), specifically the U-Net architecture, this system aims to enhance detection accuracy and efficiency.

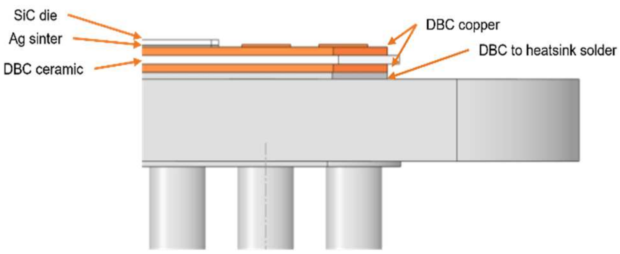

Fig. 1. SSDC Module Structure

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The AI system processes X-ray images, accurately differentiating void pixels from the background and produce inference results indicating the voids consists in the module, thus reducing the need for human intervention. Preliminary results show over 80% accuracy in defect detection and 85% in classifying various solder voids [7]. The study aims to boost the reliability and quality of SSDC SiC modules while cutting production costs and time. By integrating AI with X-ray inspection, a new standard for semiconductor manufacturing is established, improving quality management and operational efficiency. This paper outlines the development and testing of the AI system and its potential impact on the industry.

II. U-NET MODEL DEVELOPMENT

The U-Net model, renowned for its effectiveness in biomedical image segmentation, is ideal for solder void detection in SiC power modules due to its encoder-decoder architecture with skip connections, which facilitate precise localization and classification by leveraging multi-scale contextual information [1]. For this project, a ResNet34 backbone is integrated into the U-Net model to enhance feature extraction and segmentation accuracy.

The system processes raw images from the X-ray machine by initially cropping them to 1750 × 1250 pixels, focusing on the region of interest. These pre-processed images are fed into the U-Net model, which generates inference masks that highlight detected voids and provides the percentage of voids detected. This workflow ensures accurate and efficient defect detection, enhancing the quality control in semiconductor manufacturing. Fig. 2 shows the flow from the X-ray images to the output inference mask generated by the U-Net model.

A. Dataset Images Pre-processing

Based on Fig. 3, the pre-processing method introduced to optimize the dataset maximize the effectiveness of the U-Net model in identifying and categorizing solder voids in Silicon Carbide (SiC) power modules. To focus on the Region of Interest (ROI), raw grayscale X-ray pictures (2024 × 2024 pixels) are first cropped to 1750 × 1250 pixels. Using the patchify package, these photos are divided into 256 × 256 pixel patches with a 220-pixel step size. The resulting overlapping patches improve the resilience of the model and the diversity of the dataset. Consequently, each image produces precisely 35 patches, for a total of 3535 patches from 101 X-ray images.

Data augmentation increases dataset size and improves model performance using techniques such as rotation (up to 90 degrees), width and height shifts (up to 30%), shear (up to 0.5), zoom (up to 30%), and horizontal and vertical flipping. Pixel values are normalized to a standardized range to ensure consistent image processing and improve model convergence. The reflect fill mode handles pixels outside image boundaries. These augmentations are applied to both images and corresponding masks. The patches are split into 75% training (2651 patches) and 25% validation (884 patches). Over 1000 epochs, data augmentation expands the dataset to 2,651,000 training samples and 884,000 validation samples.

Void annotations are generated using the Labkit plugin from Fiji by ImageJ. Each 1750 × 1250 pixel image is annotated using semantic segmentation, where voids are classified as "void" and the background as "background." Post-annotation, masks are exported in TIFF format. The original images and corresponding masks are then stacked

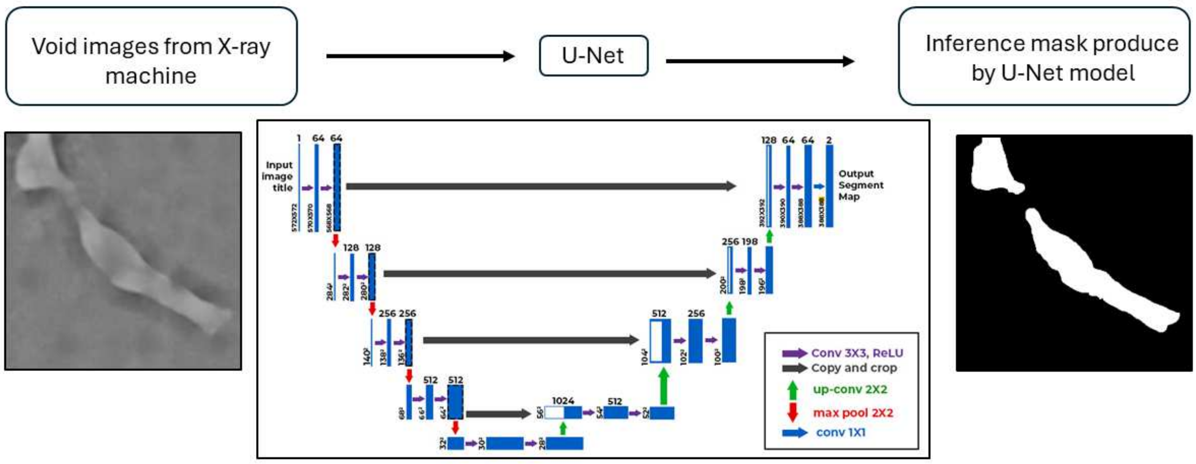


Fig. 2. Flow from the X-ray images to the output inference mask generated by the U-Net model

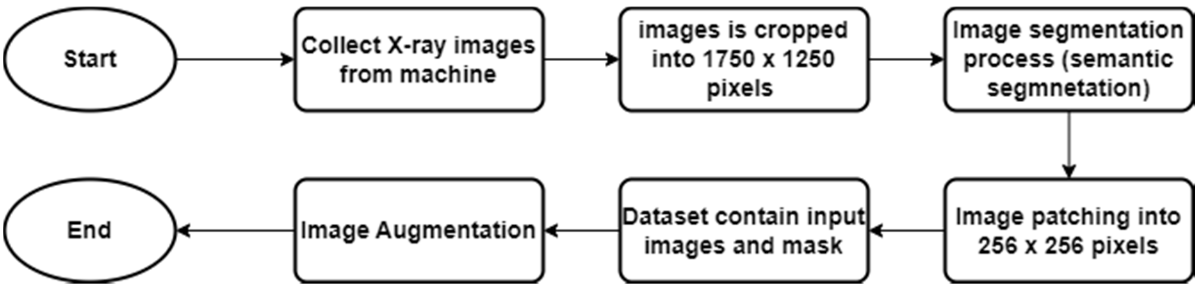


Fig. 3. Flowchart of image pre-processing

using a custom script to ensure proper pairing for the U-Net model input. These masks are binarized, with pixel values set to 0 or 1, representing background and voids, respectively.

B. Building U-Net Model

The U-Net model, enhanced with ResNet34, is defined using the segmentation models library and compiled with the Adam optimizer. The loss function employed is Binary Cross-Entropy combined with Jaccard loss, while the Intersection over Union (IoU) score serves as the primary evaluation metric.

The model is trained over 1000 epochs. Training involves steps-per-epoch and validation steps calculated based on the dataset size and batch size, enabling efficient utilization of computational resources. Throughout the training process, both training and validation losses, as well as IoU scores, are monitored and plotted to assess the model's performance and convergence. Post-training evaluation involves predicting solder voids on the test set and calculating the IoU score to quantify segmentation accuracy. The final trained model achieves high segmentation precision, significantly improving the reliability and efficiency of defect detection in semiconductor manufacturing. This rigorous approach to model development ensures that the U-Net with ResNet34 backbone is well-suited for the demands of high-precision solder void detection.

III. Experimental Results

A. Intersection over Union (IoU)

Based on Table I, the U-Net model with a ResNet34 backbone with the dataset of 101 was evaluated over various epochs to determine optimal training duration and accuracy improvements. The Intersection of Union (IoU) score, a critical metric for segmentation accuracy, showed a consistent increase from 64.00% at 200 epochs to 84.09% at 2000 epochs, highlighting the model's enhanced proficiency in detecting solder voids with extended training.

Training time per step increased slightly from 115 seconds at 200 epochs to 128 seconds by the 1000th epoch, reflecting the added computational complexity. Consequently, total training time rose significantly from 6.39 hours at 200 epochs to 71.11 hours at 2000 epochs.

A significant IoU improvement was observed up to 1000 epochs, achieving 78.31%. Beyond this, although the IoU score continued to improve, the rate of increase diminished despite substantial increases in training time. Training for 1000 epochs already provides a substantial accuracy boost, making it a practical choice. However, training up to 2000 epochs, while yielding the highest IoU of 84.09%, involves significantly longer training times, which may not be feasible for all applications.

B. Void Percentage

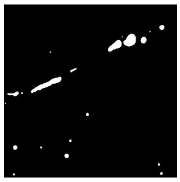
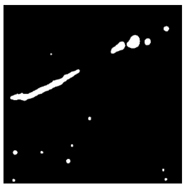
The performance of the U-Net model with a ResNet34 backbone in detecting solder voids was evaluated over different training epochs, compared to a benchmark set by manual semantic segmentation annotation. The difference is calculated by subtracting the percentage of voids detected by the model from the perfect manual annotation, which is 2.44%. Equation (1) shows the formula for calculating void percentage, where the void percentage (%) is obtained by dividing the number of white pixels by the total number of pixels. For the benchmark void percentage, this calculation was based on 3904 white pixels out of a total of 160000 pixels, resulting in 2.44% void. Table II shows the void percentage of the image for different numbers of epochs.

$$Void\ Percentage\ (\%) = \frac{White\ Pixel}{Total\ Pixel} \tag{1}$$

TABLE I. IoU Score For Difference Number of Epochs

Epochs	**IOU score**	**Time(s/step)**	**Total time(hr)**
200	64.00%	115	6.39
400	69.96%	118	13.11
600	72.35%	120	20.00
800	75.83%	125	27.78
1000	78.31%	128	35.56
1500	81.91%	128	53.33
2000	84.09%	128	71.11

TABLE II. Void Percentage for Difference Number of Epochs

IOU Score	Images	Void percentage
BENCHMARK		2.44% Voids
64.00% 200 epochs		1.68% Voids
75.83% 800 epochs		2.39% Voids
78.31% 1000 epochs		2.79% Voids
84.09% 2000 epochs		2.55% Voids

between model predictions and manual annotations across various epochs. The lowest average difference was observed at 800 epochs, indicating high performance and minimal deviation from the benchmark at this point. Beyond 800 epochs, the improvements in average difference were marginal, with the lowest value recorded at 0.03.

The voids, or white pixels, were extracted and their percentage calculated using GIMP software. The output images from the model were input into GIMP, and a threshold was applied to isolate the white pixels. The histogram function in GIMP was then used to read the pixel values and calculate the void percentage. As shown in Table II, the model's IoU scores and corresponding void detection accuracy improve with increased training epochs. At 64.00% IoU, the model detects 1.68% voids, resulting in a difference of 0.76% from the benchmark. This stage indicates the model's initial underperformance and the necessity for further training. At 75.83% IoU, the model's detection improves significantly, identifying 2.39% voids with a minimal difference of 0.05% from the benchmark, indicating the model's enhanced capability to detect solder voids.

At 78.31% IoU, the model detects 2.79% voids, resulting in a -0.35% difference from the benchmark, suggesting the model's high sensitivity to voids. Finally, at 84.09% IoU, the model achieves its highest detection accuracy, identifying 2.55% voids with a -0.11% difference from the benchmark. This close approximation to the benchmark highlights the model's high proficiency and reliability in detecting solder voids. The results demonstrate a clear correlation between increased IoU scores and improved void detection accuracy. As training epochs increase, the model becomes more proficient at identifying voids, with the difference from the benchmark reducing significantly. In the early training phase (64.00% IoU), the model struggles with under-detection, indicating insufficient learning. By the mid-training phase (75.83% IoU), significant improvements are observed, with detection rates closely matching the benchmark. In the later training phases (78.31% and 84.09% IoU), the model shows high sensitivity and minimal differences from the benchmark, indicating robust performance.

These findings have significant practical implications for the detection of SSDC SiC modules, where accurate detection of solder voids is crucial for quality control. By training the U-Net model for an optimal number of epochs, a balance between training time and detection accuracy can be achieved, ensuring reliable and efficient defect detection.

C. *Model Evaluation Using XBar & R Chart*

To evaluate the performance of the U-Net model with a ResNet34 backbone, XBar and R charts were utilized to assess consistency and accuracy across different training epochs. XBar and R charts are essential tools in quality control, used to monitor process stability and variability. The XBar chart tracks the average values of a sample over time, while the R chart monitors the range within those samples. These charts are particularly useful in detecting deviations or variations in a process, ensuring it remains within control limits. Fig.4 shows XBar & R Chart of data 3535.

From the Fig.5 and Table III, it shows distribution chart and mean value of 3535 dataset respectively, this result was based on a dataset of 3535 images, with models trained for 200, 400, 600, 800, 1000, 1500, and 2000 epochs. Each model's prediction was tested on 48 images from an X-ray machine to ensure consistent detection and accuracy. The XBar chart provided insight into the average differences

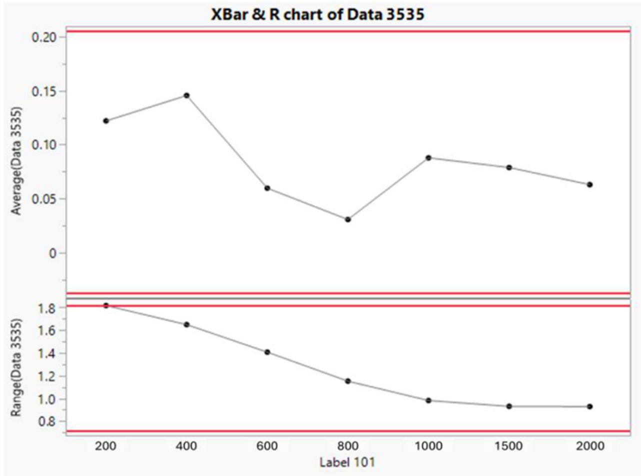


Fig. 4. XBar & R Chart of Data 3535

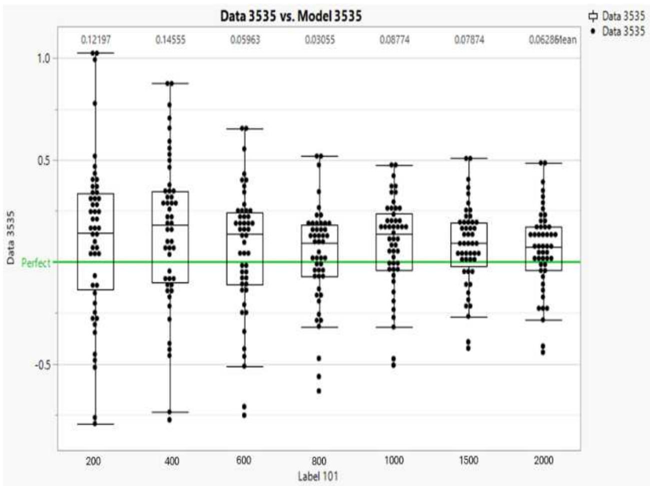


Fig. 5. Distribution Chart of Data 3535

TABLE III. MEAN FOR DIFFERENT NUMBER OF EPOCHS

3535 PATCHES DATASET	
Epochs	**Mean**
200	0.121
400	0.145
600	0.059
800	0.030
1000	0.087
1500	0.078
2000	0.062

The R chart demonstrated a steady decrease in the range of differences from 1.8 at 200 epochs to approximately 1.2 at 2000 epochs. These decreases signified improved stability and reduced variability in the model's performance as training progressed. The consistent reduction in range indicated that the model's predictions became more reliable and less variable with increased training epochs.

Box plot analysis further reinforced these findings, showing that the distribution of differences improved with increased epochs. At 800 epochs, the box plot revealed the smallest interquartile range (IQR) and a median difference closest to zero, confirming optimal performance. Additionally, the number of outliers reduced with increasing epochs, indicating fewer significant deviations from the benchmark and decreased overall variability.

The application of XBar and R charts provided a comprehensive understanding of the model's stability and accuracy over different training durations. The analysis confirmed that training the U-Net model for 800 epochs strikes the best balance between accuracy and consistency. The input data for generating these charts, based on predictions from models trained at various epochs, ensured consistent detection and accuracy, further solidifying the findings. The use of XBar and R charts was instrumental in identifying the optimal training duration for the AI model, ensuring its effectiveness in practical applications.

IV. Conclusion

This study highlights the significant potential of integrating AI with traditional X-ray inspection to enhance solder void detection in SSDC SiC modules. Using a U-Net model with a ResNet34 backbone, the AI system effectively differentiates void pixels from the background in X-ray images, significantly improving detection accuracy and reliability. The model was rigorously trained across various epochs (200, 400, 600, 800, 1000, 1500, and 2000) on a dataset of 3535 images. Performance was evaluated with XBar and R charts, which monitor process stability and variability. Performance was assessed using XBar and R charts, crucial for monitoring process stability and variability. These charts provided comprehensive insights into the model's consistency and accuracy over different training durations. The analysis revealed that training the model for 800 epochs offered the best balance between accuracy and consistency. At this point, the model showed the lowest average difference from the benchmark, high performance, and minimal deviation. The range of differences steadily decreased with increased training epochs, indicating improved stability and reduced variability. The Intersection over Union (IoU) score, a key metric for segmentation accuracy, improved consistently with more training, reaching 75.83% at 800 epochs and 84.09% at 2000 epochs. However, the most significant improvement was up to 1000 epochs. Box plot analysis confirmed these results, showing the smallest variability and median difference closest to zero at 800 epochs. Overall, combining AI with X-ray inspection greatly improved solder void detection, reducing false positives and negatives. XBar and R charts helped identify the optimal training duration, ensuring the AI model's effectiveness and reliability. These improvements enhance quality control in semiconductor manufacturing, boosting SSDC SiC modules' performance and reliability. The findings highlight AI's potential in industrial settings, promising better quality management and efficiency. Future work will refine the model and explore its use in various semiconductor manufacturing processes to set a new standard in defect detection and quality assurance.

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