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TAKE A LOOK INSIDE
Industry Briefs
—see page 10

KEY DATES
For a list of meetings
—see page 11

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Have we enabled the robots to take over?

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EDITORIAL

Have we enabled the robots to take over?

Steve Renwick, *Nikon*

That machine-learning software is great stuff. The number of Photomask and Advanced Lithography conference papers on the subject has been steadily increasing since 2014. Machine learning and its cousin, deep learning, are used for topics like locating defects to SEM image denoising to generalized tool performance enhancement. It's a good tool.

Out in the "normal" world, it's all over the place — for instance, language recognition by a computer is an everyday thing. Last year, when I was riding in a taxicab to the Tokyo airport, the driver spoke into his phone in Japanese and held it up to me, whereby it announced that there was a traffic jam ahead, but he still thought that we would make it on time.

As anyone who reads the newspaper knows, though, that's not much when compared to recent advances in artificial intelligence. The ChatGPT software was meant as an advanced internet search tool, providing results in ordinary conversational English, but people have found that they can have it write a song, a sonnet, a speech, or (and it was easy to see this coming) a term paper. Moreover, as I write this, the *New York Times* reported a "conversation" with Chat GPT's sibling Bing that got downright creepy. The reporter brought up the subject of Carl Jung's "shadow self," which contains our darkest fantasies and desires. The chatbot apparently has one and was willing to show it, first by explaining a number of ways to hack the internet (which it then erased from the screen) and second by announcing that it was in love with the reporter.

I am not certain whether any of us have gone down that particular road. At least I haven't seen any such efforts in the Digital Library yet.

We're partially responsible here. The chips and circuits made possible by our efforts are needed for AI to work. It's great to take partial credit for a phone app that helps a tourist to avoid getting lost, but we need to think about the dark side as well. Have we unloosed some evil force on the world?

Probably not. I've read the prose that ChatGPT cranks out in response to a query, and it sounds exactly like one of my junior high school textbooks: bland, faintly patronizing, and without a single original word.

Unfortunately, that's also true of us humans. Much of what we read and see now, especially on the Web, is nothing more than a rehashing and repetition of others' ideas. That's nothing to be ashamed of, as it's how we learn. Eventually, though, we need to add a real spark of creativity.

That's why these are tools and only tools. ChatGPT may be able to make creepy conversation, but it's never going to express an original thought. AI used in our field will find hotspots in OPC, but it couldn't ever invent a phase-shift mask. The rise of AI, which we helped to create, simply requires us to be better at that which makes us human.

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FEATURED ARTICLE

Towards improving challenging stochastic defect detection in SEM images based on improved YOLOv5

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ABSTRACT

With the progression of deep learning algorithms in computer vision, a lot of research is taking place in the semiconductor industry toward improving real-time defect detection and classification analysis. An Automated Defect Classification and Detection (ADCD) framework not only enables rapid measurement of dimensions and classification of defects but also helps minimize production costs, engineering time as well as tool cycle time associated with the defect inspection process. As we continue to shrink the pitch (below 36nm), defect characterization at the wafer scale becomes a key issue as it demands rapid measurement but without losing accuracy and repeatability. Also, in the context of high NA lithography (thin resist), accurate metrology becomes difficult with very noisy as well as low contrast images (No BKM exists till now). Human eyes generally demonstrate close to the Bayesian Error limit in detecting smaller objects (for example, extracting contextual information instantaneously from nanoscale defects in SEM images). However, for most One-stage and Two-stage object detectors, this is still a very challenging task due to variable image resolution and SEM (scanning electron microscope) image quality (low SNR). In this research work, we have experimented with different modified YOLOv5 object detectors to improve challenging stochastic defect detection precision. In this work, we have proposed an ensemble strategy by empirically combining multiple custom-trained models (YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x) together at the test and inference time. We have noticed four YOLOv5 architecture variants are outperforming our previous Ensemble ResNets model with improvements in the average precision metric (AP) of the most difficult defect classes as p gap and microbridges as well as overall mAP accuracy. With Ensemble YOLOv5, the p gap AP and microbridge AP matrices have been improved by 35% and 25.33%, respectively, whereas the overall mAP has been improved by 6.25%. The proposed Automated Defect Classification and Detection (ADCD) framework can also be used for high-resolution and high-speed metrology, providing rapid identification of defects with improved certainty and further root cause investigation.

Defect Category	Labeled as
Bridge	bridge
Line-Collapse	line collapse
Gap/Line-Breaks	gap
Micro/Nano-Bridge	microbridge
Probable Nano-Gap	p gap

Table 1. Defect class labeling convention.

Introduction

Moore's law has driven the semiconductor industry to shrink circuit patterns to smaller and smaller dimensions. This brings challenges for semiconductor defect inspection and metrology which are crucial for maintaining high production yield. The two main methods of inspection are optical inspection and e-beam inspection. Recently, ebeam based inspection has become more pertinent for extremely small defect detections. For inspection, e-beam is often more sensitive when compared to optical, but classification remains a challenge for both methods. Also, defect location accuracy is better for e-beam-based tools which are often linked to design databases. Even though resolution and location accuracy improves greatly with e-beam tools, the absence of robust classification algorithms often requires engineers to manually classify defects, thereby, increasing associated engineering time.

Continuous shrinking of circuit patterns is enforcing difficulty for conventional defect inspection procedures and often leads to false defect detections and erroneous metrology. Machine learning/Deep learning-based algorithms and approaches have empirically shown improvement over conventional detection algorithms.[1] In our previous research work,[2,3] we have proposed an ensemble of ResNet models (as ResNet50, ResNet101, and ResNet152, etc.) to detect and classify different types of defects in e-beam inspection images (more specifically, After Develop Inspection (ADI)) accurately and robustly. These defect types are summarized in Table 1 and some of them are depicted in Fig. 1 [(a)-(d)].

In this research paper, we have iterated our previous work[2,3] to experiment with further improvement possible with challenging stochastic defect detection, especially with (a) p gap and (b) microbridge, as well as overall mAP metric for all defect types. In summary, the major contribution of this work is:

We have individually trained 5 different YOLOv5[4] architecture variants with identical training data, keeping all experimental conditions the same as the previous ensemble strategy.[2,3] We have also proposed a similar ensemble strategy by empirically combining

multiple custom-trained models (YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x) together at the test and inference time. We have noticed four YOLOv5 architecture variants are outperforming the proposed Ensemble ResNets model with an improvement of the average precision metric (AP) of the most difficult defect classes as p gap and microbridges as well as overall mAP accuracy. With Ensemble YOLOv5, the p gap AP and microbridge AP matrices have been improved by 35% and 25.33%, respectively, whereas the overall mAP metric has been improved by 6.25%. Therefore, we have validated our "data-centric approach" instead of a "model-centric approach", where we carefully labeled all our custom datasets to balance the trade-off between "data quantity" vs. "data quality". The consistency between the overall mAP of the prior Ensemble ResNets model and the proposed Ensemble YOLOv5 architecture can be established as a proof-of-concept as a balanced trade-off between the "data-centric approach" and the "model-centric approach". The remainder of the paper is organized as follows. In Sec. 2, we have discussed some recent research approaches toward semiconductor defect detection and analysis using conventional and/or deep learning algorithms. In Sec. 3, we have provided an overview of YOLOv5 architecture variants and our proposed ensemble method. Sec. 4 demonstrates the experiments done followed by Sec. 5 including the performance evaluation and comparison analysis. In Sec. 6, we conclude the paper.

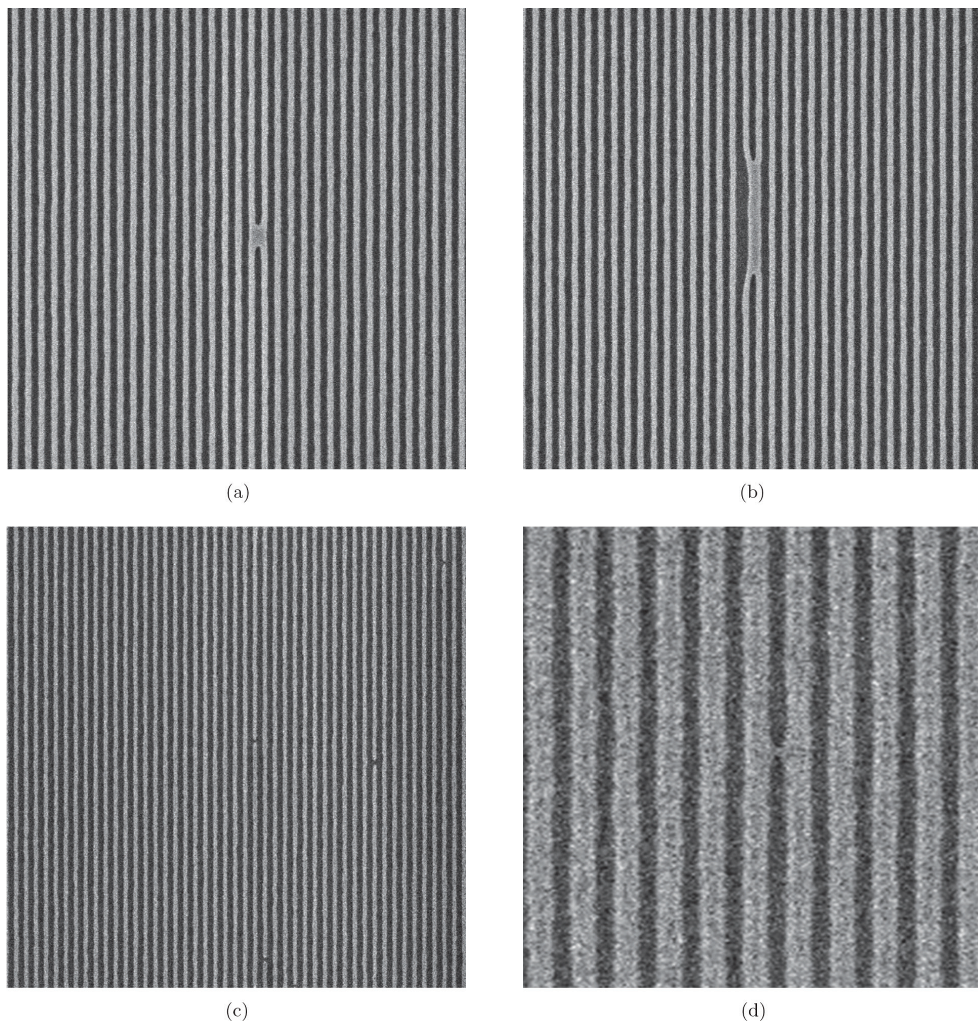

Figure 1. Typical Defects: (a) Bridge, (b) Line-Collapse, (c) Gap and Prob-Gap, and (d) Micro-bridge.

Related Work

In this section, we have briefly reviewed a few recent works on semiconductor defect inspection using machine learning. In,[5] the authors proposed a classical-quantum hybrid algorithm approach for deep learning-based semiconductor defect review. Their fine-tuned framework is capable to learn wafer defect map classification, defect pattern classification, and hotspot detection. They have also explored parametrized quantum circuits with several expressibility and entangling abilities. S. Nag et al.[6] have proposed a lightweight deep learning model as "WaferSegClassNet" (WSCN) for the classification and segmentation of semiconductor wafer defects. To increase the accuracy and decrease model training time, the authors utilized N-pair contrastive loss mechanism. K. Maksim et al. in[7] have proposed a DCNN model for identifying patterns of defects in semiconductor wafers. They created synthetic data and trained the model along with a small amount of experimental data. In,[8] authors proposed a useful framework as a single shot detector for the detection of mixed-type defect patterns, which in general, concurrently occur in a wafer bin map. T. Schlosser et al.,[9] have proposed a novel hybrid multistage system of stacked deep neural networks, as "SH-DNN", which allows localization of small defect patterns (few μm) on the much larger wafer surface. An extensive discussion, of existing research approaches and methodologies in the context of machine learning-based defect inspection, have already been presented in our prior research works.[2,3]

Proposed Approach

In this section, our proposed approach, based on the YOLOv5 detector,[4] to detect different defects from SEM images and classify them according to their corresponding classes in aggressive pitches is presented. YOLOv5 architecture has five

architecture variants as YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, respectively. YOLOv5 implementation is an incremental improvement of its predecessor models like the recent YOLOv3[10] and YOLOv4,[11] which is a target detection algorithm based on regression. The key features can be highlighted as a mosaic data augmentation strategy, auto-learning bounding box anchors, cross-stage partial network, and adaptive image filling. The architecture functionality is distributed into four segments: (a) input, (b) backbone, (c) neck, and (d) output, respectively. The backbone network consists of CSP (cross-stage partial network) and SPP (spatial pyramid pooling), which helps to extract feature maps of distinct sizes. The neck network utilizes FPN[12] and PAN[13] structures, which have an inverse strategy. While the former is responsible to propagate strong semantic features from (top→lower) feature maps, the latter propagates strong localization features in the opposite way. The detection capability of the model is improved due to the mutual enhancement of the features, extracted from different network layers in backbone fusion. Fig. 2 demonstrates the proposed Ensemble YOLOv5-based ADCD (Automatic Defect Classification and Detection) framework. We have used only real wafer data (ADI SEM images) to train and evaluate the framework. For inference, the framework is tested using imec datasets (both Post-Litho and Post-Etch resist Wafer dataset), which demonstrates its effectiveness both quantitatively and qualitatively.

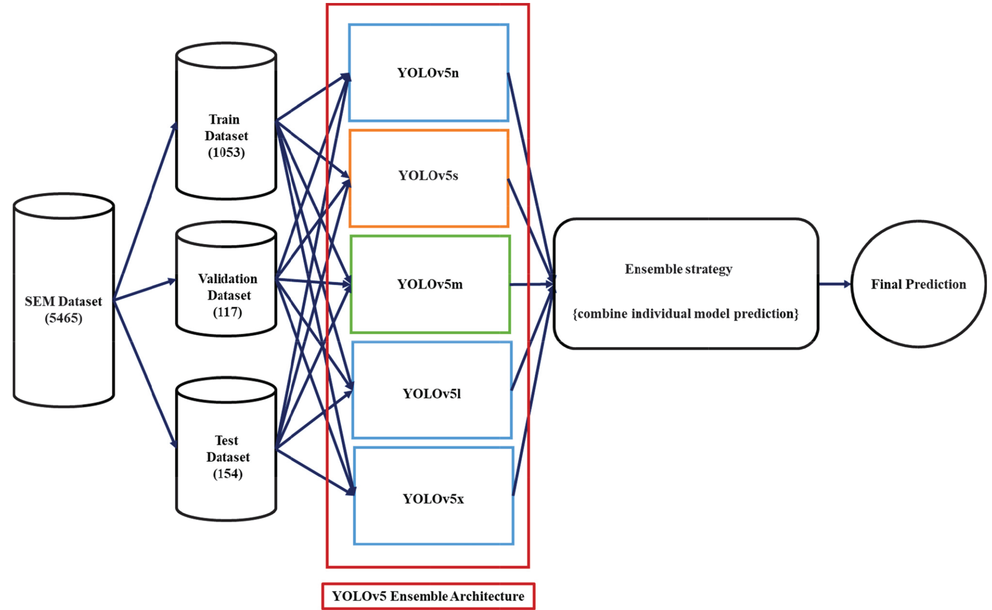

Figure 2. Proposed Ensemble YOLOv5-based ADCD framework.

Class Name	Train (1053 images)	Val (117 images)	Test (154 images)
gap	1046	156	174
p gap	315	49	54
microbridge	380	19	78
bridge	238	47	17
line collapse	550	66	76
Total Instances	2529	337	399

Table 2. Data distribution of defect SEM images.

Features	Model Name				
	YOLOv5n	YOLOv5s	YOLOv5m	YOLOv5l	YOLOv5l
#layer	213	213	290	367	444
#paramaters	1765930	7023610	20869098	46129818	86200330
#GFLOPs	4.2	15.8	48.0	107.9	204.1
NMS speed (seconds per image)	0.0008	0.0007	0.0007	0.0008	0.0007

Table 3. Summary of YOLOv5 architecture variants.

EXPERIMENTS

Our proposed defect detection framework is trained on Lambda TensorBook with NVIDIA RTX 2080 MAX-Q GPU, using PyTorch library[14] backend in the python programming environment.

Datasets

The dataset used in this study is reused from[2,3] as demonstrated in Table 2. We have manually labeled all images according to different defect categories to be used as training and validation sets. Examples of these defect types are shown in Fig. 1 [(a)-(d)]. The motivation of this research is that we found probable gaps and microbridges (which are small compared to the other defect types) were particularly challenging for prior RetinaNet-based detectors.[2,3]

We have investigated with a "model-centric approach" by developing experimental research to improve our defect detection framework performance, which involved selecting the best model(s)/backbone architecture(s) (training dataset must be the same) and training process from a comprehensive range of prospects.

Evaluation criteria

We have considered Intersection over Union (IoU)[15] between the ground truth bounding box and the predicted bounding box 0.5. The "defect detection confidence score" metric is taken as 0.5. The proposed ensemble model-based (Ensemble YOLOv5 architecture) defect detector's overall performance is evaluated against mAP as Mean Average Precision, where mAP is calculated using the weighted average of precisions among all defect classes. AP or average precision provides the detection precision for one specific defect class. We have also considered the speed of detection per image (average-inference-time in seconds).

Training

We have first trained five different YOLOv5 architectures experimentally as YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x with identical training data, keeping all experimental conditions the same as previous ensemble strategy.[2,3] Table 3 provides the summary for architecture variants with the total number of layers, the total number of trainable parameters, NMS (Non-maximum Suppression) speed per image, and GFLOPs metric, respectively. Table 4 provides the comparison analysis for defect detection accuracies obtained per defect class as well as mAP on training images for the above experimental architectures with a score threshold of 0.50, with AP50. Table 5 provides the comparative analysis for the same on validation and test images. YOLOv5s is outperforming all the previous backbone architectures as well as other YOLOv5 architecture variants for p gap defect with 70% average precision (AP). We have noticed four YOLOv5 architecture variants (as YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x) are outperforming all the previous backbone architectures as well as the proposed Ensemble ResNets model with an improvement of the average precision metric (AP) of the most difficult defect classes as p gap and microbridges as well as overall mAP accuracy. With Ensemble YOLOv5, the p gap AP and microbridge AP metric have been improved by 35% and 25.33% respectively, whereas overall mAP accuracy has been improved by 6.25%, as presented in Table 6. There is further scope for improvement of the overall mAP metric by retraining the architectures with more training data with similar types of defects as well as through hyperparameters evolution strategy.

Class name	YOLOv5n	YOLOv5s	YOLOv5m	YOLOv5l	YOLOv5x
gap AP	0.975	0.98	0.983	0.983	0.988
p-gap AP	0.372	0.498	0.529	0.53	0.55
bridge AP	0.929	0.941	0.951	0.963	0.98
microbridge AP	0.822	0.823	0.849	0.843	0.899
line collapse AP	0.989	0.993	0.993	0.993	0.993
mAP	0.817	0.847	0.861	0.862	0.882

Table 4. Evaluation results on the training images when experimenting with different YOLOv5 architectures. (AP @ 0.5 IOU).

Split	Class Name	YOLOv5n	YOLOv5s	YOLOv5m	YOLOv5l	YOLOv5x
Vat	gap AP	0.953	0.966	0.974	0.977	0.986
	p gap AP	0.535	0.544	0.564	0.599	0.62
	bridge AP	0.862	0.974	0.962	0.963	0.974
	microbridge AP	0.935	0.914	0.938	0.956	0.964
	line collapse AP	0.995	0.995	0.995	0.995	0.995
	mAP	0.856	0.879	0.887	0.898	0.908
	Mean inference time (s/image)	0.005	0.0091	0.0213	0.0358	0.0648
Test	gap AP	0.963	0.972	0.97	0.973	0.974
	p gap AP	0.472	0.706	0.695	0.68	0.698
	bridge AP	0.688	0.811	0.764	0.786	0.817
	microbridge AP	0.803	0.784	0.828	0.815	0.851
	line collapse AP	0.991	0.994	0.995	0.995	0.995
	mAP	0.783	0.853	0.851	0.85	0.867
	Mean inference time (s/image)	0.005	0.0088	0.0212	0.0356	0.0649

Table 5. Validation/test precision results of the five different YOLOv5 architecture variants. A confidence score threshold of 0.5 was used.

Class name	Ensemble YOLOv5	Ensemble ResNet[2,3]
gap AP	0.973	0.959
p gap AP	0.702	0.52
bridge AP	0.818	0.867
microbridge AP	0.846	0.675
line collapse AP	0.995	0.828
mAP	0.867	0.816

Table 6. Overall test accuracy of Ensemble YOLOv5 framework against Ensemble ResNet framework.

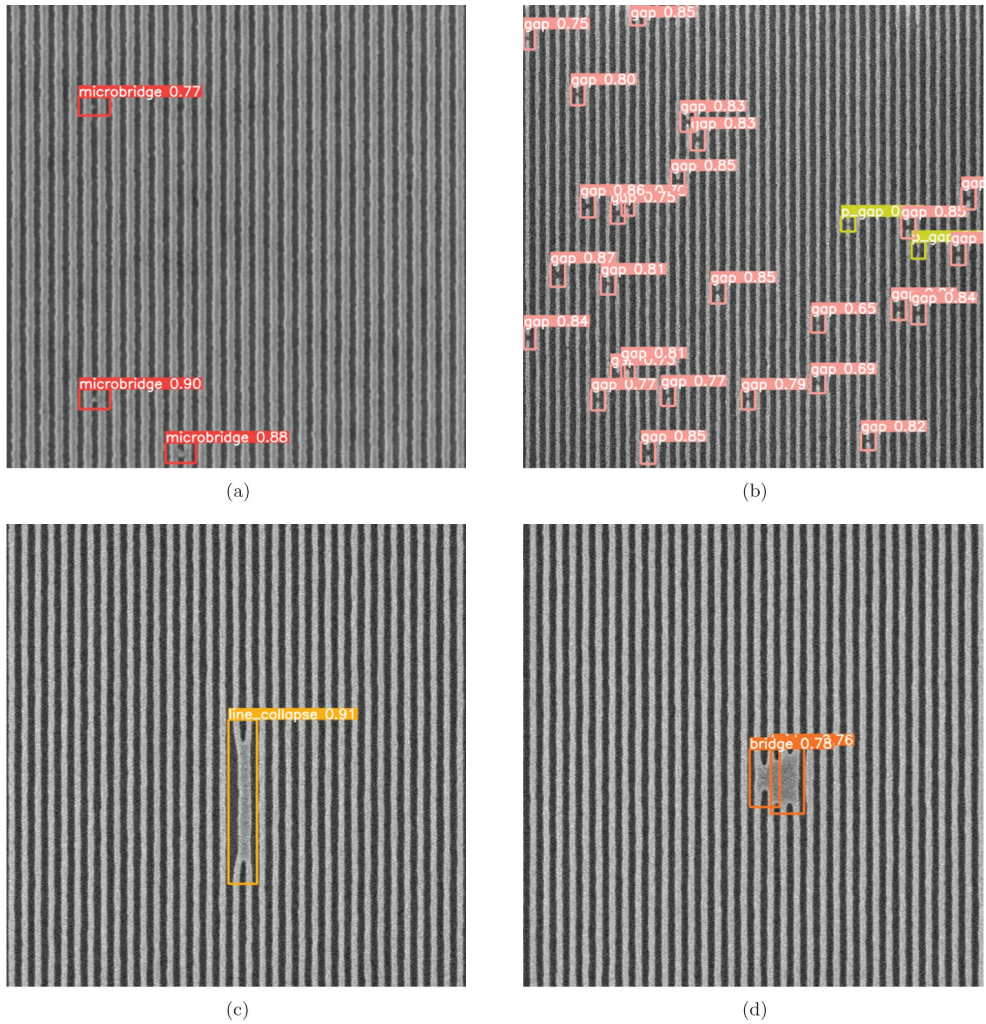

Figure 3. Defect detection visualization with YOLOv5x model. (a) Nanobridge/ micro-bridge effectivity. (b) Single Gap/Break, (c) Single Line-Collapse, and (d) Multiple Bridges.

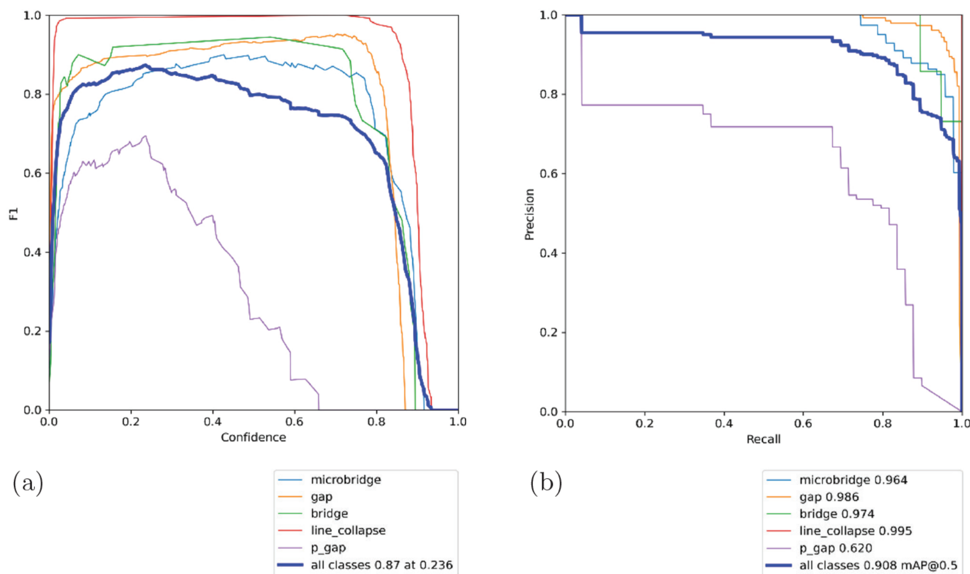

Figure 4. (a) F1-score, (b) Precision-Recall curve of the test and validation data with YOLOv5x model.

EVALUATION

Defect detection performance

Our proposed Ensemble YOLOv5 architecture-based defect detection framework achieves the detection precision (AP) of 97.3% for a gap, 81.8% for a bridge, 99.5% for line collapse, 84.6% for a microbridge, and 70.0% for probable nano-gap defectivity, respectively. Fig. 3 [(a)-(d)] illustrates the detection of more challenging nano bridges/ microbridges defectivity, nano-gaps and probable nano-gaps, line-breaks, and multi-bridges with the YOLOv5x model. Fig. 4 (a) demonstrates the F-measure of the YOLOv5x model, the confidence value that optimizes the precision and recall is 0.236 for the test dataset, whereas Fig. 4 (b) Precision determines how much the bbox predictions are accurate and Recall determines how much of the true bbox were appropriately anticipated. In Fig. 5 (a), the confusion matrix of the YOLOv5x model is shown. It can be noticed that the confusion between different types of defects is lower except for probable nano-gap defect class, which is apparent as the training instances are very limited for this specific defect category as well as there are misjudgments between true gaps, probable nano-gaps, and the background. A data augmentation strategy can be adopted to increase the gap between these classes to further improve detection precision. Fig. 5 (b) demonstrates different losses and metrics during the training of the model. In future work, we need to improve on detecting specific classes like a bridge, microbridge, and probable nano-gap. This will also improve the overall mAP of the proposed framework can also be improved. This will be considered the next step of this research.

FEATURED ARTICLE

CONCLUSION

In this work, we have trained 5 different YOLOv5 architecture variants and performed a comparative analysis on individual defect class accuracy as well as overall mAP accuracy against the prior Ensemble ResNets model. Nearly all YOLOv5 architecture variants are outperforming the proposed Ensemble ResNets model with an improvement of the average precision metric (AP) of the most difficult defect classes as p gap and microbridges as well as overall mAP accuracy. With the Ensemble YOLOv5 model, the p gap AP and microbridge AP matrices have been improved by 35% and 25.33%, respectively, whereas the overall mAP metric has been improved by 6.25%. There is further scope for improvement of the overall mAP metric by retraining the architectures with more training data with similar types of defects as well as through hyperparameters evolution strategy.

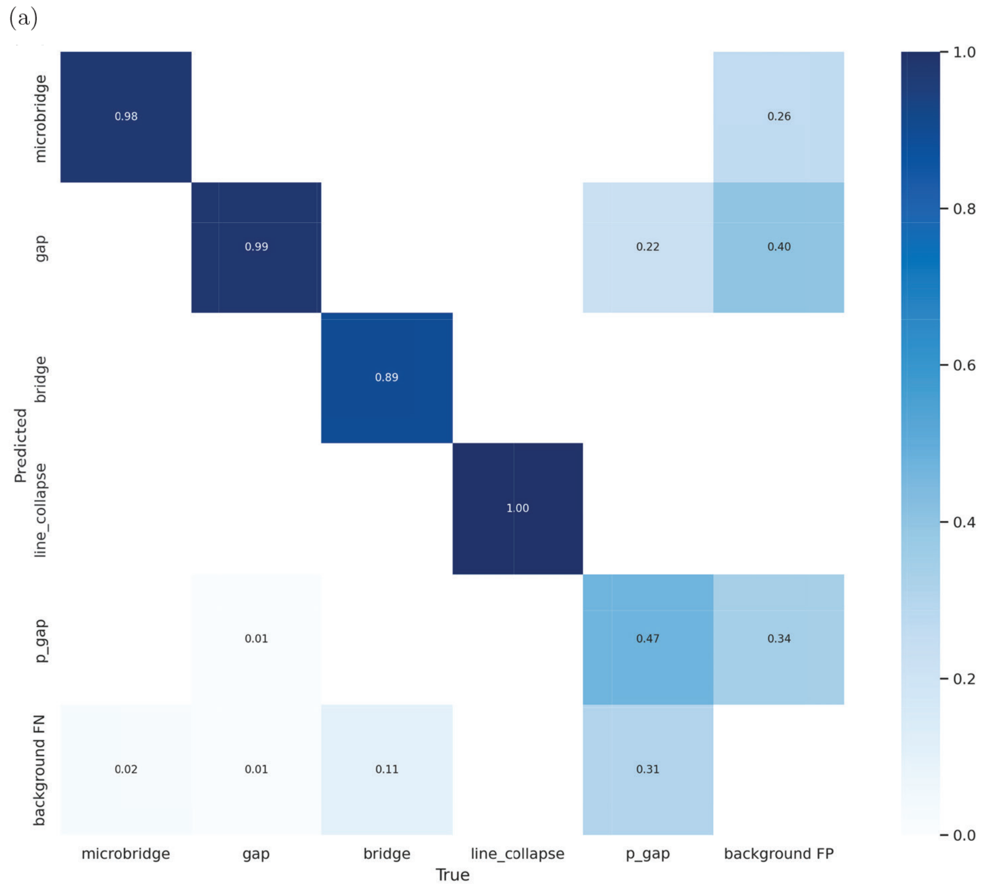

Figure 5. (a) Confusion matrix of YOLOv5x model. (b) YOLOv5x model losses and metrics during training.

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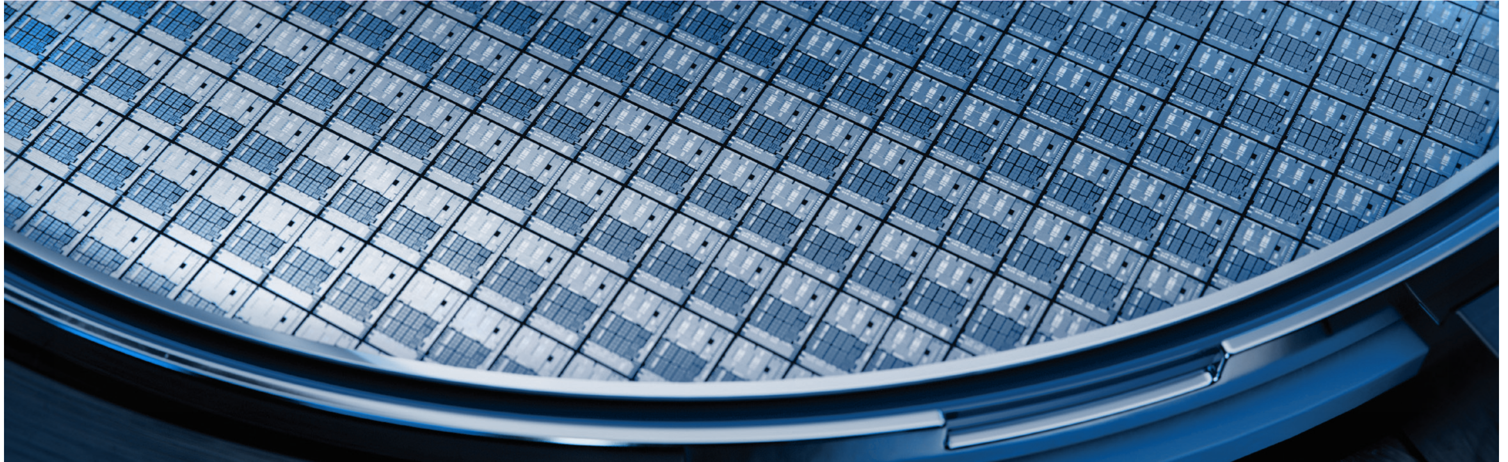

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INDUSTRY BRIEFS

AI-Powered Chip Design Goes Mainstream (Feb 10, 2023)

Not only can AI design better chips than human engineers, but we will need AI to keep up with future increases in device complexity—just like we needed design automation 35 years ago, Synopsys CEO Aart de Geus said. Synopsys customer Hynix was able to not only increase productivity using design space optimization, but also reduced die size for its design by 5%.

https://www.eetimes.com/ai-powered-chip-design-goes-mainstream/

How Europe Hopes to Counteract the Semiconductor Shortage (Feb 13, 2023)

Carmakers have been disrupted over the past three years as they faced forces beyond their control. Manufacturers are eager to snap up semiconductor deals as demand is predicted to increase. German car body VDA reiterated this message in a recent study, which projects semiconductor demand in the automotive industry will triple by 2030.

https://autovista24.autovistagroup.com/news/how-europe-hopes-to-counteract-semiconductor-shortage/

GM, GlobalFoundries Sign Chip Supply Deal (Feb 9, 2023)

GM and chip maker GlobalFoundries reached an agreement to supply semiconductors for the automotive company. “We see our semiconductor requirements more than doubling over the next several years as vehicles become technology platforms,” said Doug Parks, GM executive vice president of global product development, purchasing and supply chain.

https://www.wsj.com/articles/gm-builds-semiconductor-pipeline-with-globalfoundries-partnership-11675968495

Micron Announces 2024 Start for Construction on Clay Semiconductor Plant (Feb 12, 2023)

Micron Technology announced it will begin construction in 2024 on its Clay facility in New York. The semiconductor manufacturer’s pledge of up to $100 billion by 2030.

https://dailyorange.com/2023/02/micron-announces-2024-start-for-construction-on-clay-semiconductor-plant/

The Bill for CHIPS Subsidies Comes Due (Feb 13, 2023)

Senators want the Commerce Department to ban stock buybacks for semiconductor companies that receive funding from CHIPs.

https://www.wsj.com/articles/chip-subsidies-stock-buybacks-elizabeth-warren-senate-democrats-letter-tammy-baldwin-bernie-sanders-bf10e5b0?st=mvm2we4shyh1qlt&reflink=article_gmail_share

British Semiconductor Bosses Threaten to Move Overseas as U.S. and EU Splurge on Chips (Feb 13, 2023)

Britain is an understated player in the global chip market, specializing in design, intellectual property, research and fabrication of compound semiconductors. The U.K.’s semiconductor industry is crying out for financial support from the government, with insiders warning the country risks losing its microchip firms to the U.S. and other countries if it doesn’t act soon.

https://www.cnbc.com/2023/02/13/uk-semiconductor-strategy-chip-firms-threaten-to-move-overseas.html

Google Has Developed Its Own Data Center Server Chips (Feb 14, 2023)

After the Tensor Processing Unit as an ASIC designed to accelerate AI and neural network machine learning, Google has made significant progress in its endeavor to develop its own data center chips reported to be rolled out in 2025.

https://www.tomshardware.com/news/google-reaches-self-developed-data-center-server-chip-milestone

Augmented Reality (AR) and Mixed Reality (MR) Market is Projected to Reach at a CAGR of 50.5% by 2029 (Feb 14, 2023)

Data Bridge Market Research forecasted that the global AR and MR market is expected to reach the value of over $600B by 2029. The hardware segment accounts for the largest component segment.

https://www.bloomberg.com/press-releases/2023-02-14/augmented-reality-ar-and-mixed-reality-mr-market-is-projected-to-reach-at-a-cagr-of-50-5-by-2029-size-share-drivers

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Founded in 1980 by a group of chrome blank users wanting a single voice to interact with suppliers, BACUS has grown to become the largest and most widely known forum for the exchange of technical information of interest to photomask and reticle makers. BACUS joined SPIE in January of 1991 to expand the exchange of information with mask makers around the world.

The group sponsors an informative monthly meeting and newsletter, BACUS News. The BACUS annual Photomask Technology Symposium covers photomask technology, photomask processes, lithography, materials and resists, phase shift masks, inspection and repair, metrology, and quality and manufacturing management.

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- Listed as a Corporate Member in the BACUS Monthly Newsletter

spie.org/bacushome

Key dates

2023

SPIE Photomask Technology and EUV Lithography
1–5 October 2023
Monterey, California, USA
www.spie.org/puv

European Mask and Lithography Conference (EMLC)
19–21 June 2023
Dresden, Germany
www.emlc-conference.com

Photomask Japan (PMJ)
25–27 April 2023
Online only
www.photomask-japan.org

You are invited to submit events of interest for this calendar.
Please send to lindad@spie.org.

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