Bibliometric study on artificial intelligence technologies for semiconductor defects

Seongeun Kim[1,2], Eunil Park[3,*]
[1]Samsung Electronics, Suwon, Korea
[2]Department of Semiconductor and Display Engineering, Sungkyunkwan University, Suwon, Korea
[3]Department of Applied Artificial Intelligence, Sungkyunkwan University, Seoul, Korea

***Abstract*—The rapid progress of science and technology, coupled with the integration of artificial intelligence, is driving transformative shifts within the manufacturing sector. Notably, artificial intelligence is playing a pivotal role in revolutionizing semiconductor manufacturing. The recent focus has been on artificial intelligence (AI)-driven methods for managing semiconductor defects. We aimed to perform a comprehensive bibliometric analysis, spotlighting trends in AI research within the semiconductor domain, particularly concerning defects. We gathered pertinent publications from Scopus and Web of Science databases, meticulously examining their distributions. Our findings encompass a total of 808 papers published between 2019 and 2023. Over this five-year span, publications exhibit consistent growth, with Proceedings of SPIE and IEEE Transactions on Semiconductor Manufacturing emerging as the most prolific sources as per Scopus and Web of Science data. Additionally, we scrutinized influential research approaches and data resources outlined in top-tier publications. The study underscores the persistent expansion of this research realm and outlines three principal insights and three extant limitations associated with employing AI for semiconductor defect control.**

***Index Terms*—bibliometric analysis, artificial intelligence, defects, semiconductor**

I. Introduction

The progress of Artificial Intelligence (AI) yields varied impacts on contemporary society, inducing substantial alterations across multiple facets of life and social frameworks. Its influence spans diverse domains, including healthcare and life sciences, autonomous driving, natural language processing, AI assistants, as well as security and cyber safety [1].

AI has already outperformed humans in specific domains, and forecasts suggest that automation will encompass approximately 50% of tasks within the next four decades, progressing towards nearly complete automation in around 120 years [2]–[4]. Within this context, AI assumes a pivotal position within the semiconductor industry. The substantial data influx from semiconductor manufacturing and research necessitates the application of data science techniques for efficient processing and analysis. Moreover, maintaining a competitive advantage hinges on effective yield management, which places paramount importance on the identification and mitigation of elements like defects and faults. Consequently, numerous researchers have delved into an array of AI methodologies to diminish and control semiconductor defects.

Aligned with this trend, we aim to conduct an exhaustive bibliometric analysis that highlights the prevailing trends in AI research within the semiconductor sphere, with a specific focus on defects. Section 2 outlines the methodologies employed in this study. The outcomes are delineated in Section 3, while Section 4 concludes with a comprehensive discussion.

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Corresponding author: Eunil Park (eunilpark@skku.edu)

II. Analysis Methods

We gathered data from two prominent citation databases: Scopus and Web of Science. Scopus, an expansive bibliographic repository, encompasses an array of academic fields. Web of Science, on the other hand, presents top-tier academic material spanning a gamut of subjects, spanning from natural and social sciences to arts and humanities. Pertinent publications, integral to our study, were extracted based on search query terms present within their titles or abstracts. Papers not authored in English or categorized as different document types were excluded. The dataset was restricted to the most recent five years (2019 to August 2, 2023; Figure 1) [5].

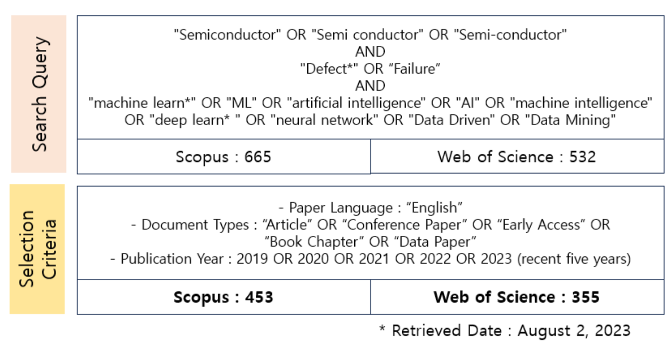

Fig. 1. Representative data collection procedure

Hence, a cumulative count of 808 papers, published within the timeframe of 2019 to August 2, 2023, was amassed. To encapsulate the swiftly evolving landscape of AI research, we also incorporated the ongoing year, 2023, which remains receptive to emergent advancements. The exhaustive compilation of encompassed publications can be found in Multimedia Appendix 1.

A bibliometric analysis entails delving into the distribution of publications, research themes, geographical origins, and citation counts. Statistical evaluations of the collected papers were executed through a combination of the Python programming language and Microsoft Excel [6]. Our initial scrutiny encompassed the dissemination of publications across diverse categories, encompassing years, countries, institutions, sources, authors, and research themes. Furthermore, we undertook a network analysis of frequently employed keywords. In addition, to pinpoint the dominant research trajectories within this domain, we conducted trend review analyses. These analyses focused on highly cited papers that encapsulated the subsequent areas: (i) AI techniques, (ii) Semiconductor, and (iii) Defects and failures.

III. Results

A. Publication Distribution Analysis

1) Overall Publication Trend: Table I illustrates the ongoing expansion of publications from 2019 to 2023 (until August 2nd). In 2019, a cumulative of 54 papers were procured from Scopus, while an additional 46 papers were sourced from Web of Science. Notably, there was a pronounced surge in publication count in 2023, yielding 86 papers from Scopus and 51 from Web of Science. Given the data retrieval date (August 2nd, 2023), it's foreseeable that further papers will be accumulated during the remainder of 2023, emphasizing the sustained surge in scholarly interest across the domains of AI, Semiconductor, and Defects.

Year	Publication count, n(%)	
	Scopus (N=453)	Web of Science (N=355)
2019	54 (11.92)	46 (12.96)
2020	72 (15.89)	63 (17.75)
2021	95 (20.97)	75 (21.13)
2022	146 (32.23)	120 (33.8)
2023	86 (18.98)	51 (14.37)

TABLE I
NUMBER OF PUBLICATIONS PER YEAR.

2) Predominant Countries: More than 30 countries emerged as leading contributors in research within this field on both Scopus (n=42) and Web of Science (n=38). Table II presents the countries with the highest publication output. China secured the top spot in both databases, followed by the United States and South Korea.

Scopus (N=453)			Web of Science (N=233)		
Rank	Country	Count, n(%)	Rank	Country	Count, n(%)
1	China	106 (23.4)	1	China	85 (23.94)
2	United States	65 (14.35)	2	United States	54 (15.21)
3	South Korea	58 (12.8)	3	South Korea	50 (14.08)
4	Taiwan	31 (6.84)	4	Taiwan	29 (8.17)
5	India	21 (4.64)	5	Germany	16 (4.51)
5	Japan	21 (4.64)	5	Japan	16 (4.51)
7	Germany	20 (4.42)	7	India	14 (3.94)
8	Singapore	18 (3.97)	8	Singapore	12 (3.38)
9	France	10 (2.21)	9	France	10 (2.82)
9	Italy	10 (2.21)	10	Italy	7 (1.97)

TABLE II
TOP PRODUCTIVE COUNTRIES.

3) Productive Institutions: A total of 633 distinct institutions were associated with the 808 publications. The predominant institutions are detailed in Table III. Significantly, the Chinese Academy of Sciences in China garners attention as the most prolific entity, significantly contributing across both databases, with 22 publications in Scopus and 36 publications in Web of Science.

Institution	Publication count, n(%)	
	Scopus (N=453)	Web of Science (N=355)
Chinese Academy of Sciences	22 (3.28)	36 (3.98)
Tongji University	10 (1.49)	9 (0.99)
Universidad de Castilla-La Mancha	10 (1.49)	13 (1.44)
Sungkyunkwan University	9 (1.34)	16 (1.77)
National Tsing Hua University	8 (1.19)	10 (1.1)
Chungbuk National University	8 (1.19)	8 (0.88)
Zhejiang University	8 (1.19)	10 (1.1)
Beijing University of Technology	7 (1.04)	7 (0.77)
Korea University	7 (1.04)	9 (0.99)
Samsung	7 (1.04)	21 (2.32)
Argonne National Laboratory	6 (0.89)	8 (0.88)
National Cheng Kung University	6 (0.89)	10 (1.1)
RMIT University	6 (0.89)	5 (0.55)
Tianjin University	6 (0.89)	6 (0.66)
Wuhan University	5 (0.75)	4 (0.44)
Engineering Research Center of Digital Community	5 (0.75)	-
Myongji University	5 (0.75)	5 (0.55)
University of Southern California	5 (0.75)	4 (0.44)
Jiangsu University	5 (0.75)	5 (0.55)
National Taipei University of Technology	5 (0.75)	5 (0.55)

TABLE III
TOP PRODUCTIVE INSTITUTIONS.

4) Productive Publication Sources: We encompassed diverse document types, encompassing not solely journal articles but also conference proceedings and book chapters. Table IV and Table V depict sources of publications that exhibit noteworthy tallies within Scopus and Web of Science, respectively. Among these sources, Proceedings of SPIE emerged as the most prolific in Scopus, boasting 33 publications, trailed by IEEE Transactions on Semiconductor Manufacturing and IEEE Access. Conversely, in Web of Science, IEEE Transactions on Semiconductor Manufacturing garnered recognition as the most prolific source, presenting 29 publications, followed by IEEE Access and Applied Sciences-Basel.

5) Predominant Authors: Table VI presents the top 10 researchers whose contributions significantly impact the field, arranged in descending order of their publication counts. Among these distinguished researchers, four maintain affiliations with esteemed institutions in Spain, while three are associated with prominent organizations in China, and one is affiliated with institutions in South Korea, Belgium, and Singapore. Additionally, a researcher hails from a renowned establishment in South Korea. Kang Seokho, affiliated with Sungkyunkwan University, stands out as the most prolific contributor, boasting seven publications. Equally noteworthy are Yu Naigong and Xu Qiao from Beijing University of Technology, as well as Yu Jianbo from Tongji University, each boasting commendable publication records.

Rank	Source	Publication count, n (%)
1	Proceedings of SPIE - The International Society for Optical Engineering	33 (7.28)
2	IEEE Transactions on Semiconductor Manufacturing	31 (6.84)
3	ASMC (Advanced Semiconductor Manufacturing Conference) Proceedings	13 (2.87)
4	IEEE Access	12 (2.65)
5	Applied Sciences (Switzerland)	9 (1.99)
6	Computers and Industrial Engineering	8 (1.77)
6	Proceedings of the International Symposium on the Physical and Failure Analysis of Integrated Circuits	8 (1.77)
8	Expert Systems with Applications	6 (1.32)
8	Journal of Intelligent Manufacturing	6 (1.32)
10	Proceedings - Electronic Components and Technology Conference	4 (0.88)

TABLE IV
TOP PUBLICATION SOURCES IN SCOPUS (N=453).

Rank	Source and publication count, n (%)
1	IEEE Transactions on Semiconductor Manufacturing, 29 (8.17)
2	IEEE Access, 12 (3.38)
3	Applied Sciences-Basel, 9 (2.54)
4	Journal of Intelligent Manufacturing, 7 (1.97)
4	Metrology, Inspection, and Process Control XXXVII, 7 (1.97)
6	Computers and Industrial Engineering, 6 (1.69)
7	Metrology, Inspection, and Process Control for Microlithography XXXVII, 5 (1.41)
8	Expert Systems with Applications, 4 (1.13)
8	Scientific Reports, 4 (1.13)
8	Annual Semi Advanced Semiconductor Manufacturing Conference (ASMC), 4 (1.13)

TABLE V
TOP PUBLICATION SOURCES IN WEB OF SCIENCE (N=355).

6) Productive Research Subjects: The top 10 research subjects of each citation database are given in Figure 2. Noteworthy is the prominence of Engineering as the primary research subject in both databases, encompassing 317 publications (28.9%) in Scopus and 210 publications (30.0%) in Web of Science. Within Scopus, Materials Science (200, 18.3%), Computer Science (198, 18.1%), and Physics and Astronomy (142, 12.9%) each exceeded the 10% threshold of total publications. Similarly, in Web of Science, Computer Science (95, 13.6%), Physics (88, 12.6%), and Materials Science (79, 11.3%) accounted for more than 10% of the total publications.

7) Keyword Co-occurrence: We conducted an in-depth investigation into the keywords provided by authors and indexing sources, complementing our analysis of research subjects. Author keywords encompass terms specifically selected by paper authors, while Index keywords are meticulously curated to accurately encapsulate paper content and characteristics. For visual representation, we harnessed a network graph, a widely employed bibliometric approach (Figure 3). Here, each node corresponds to a keyword, and an edge connecting nodes signifies co-occurrence within the same paper. To enhance precision, edges with less than 3 co-occurrences were filtered out. High-frequency keywords, such as semiconductor manufacturing, defects, silicon wafers, convolutional neural networks, and deep learning, underscore prevalent research domains. These keywords exhibit degrees of 16 or higher. Notably, keywords linked to artificial intelligence techniques encompass convolutional neural network, deep learning, machine learning, classification, pattern recognition, and image enhancement. This signals a pronounced curiosity in the implementation of artificial intelligence in the field. In the context of semiconductor-related keywords, notable terms encompass silicon wafers, wafer map, and semiconductor wafer, underscoring a research focus primarily centered around the wafer level.

B. Overview of Highly Cited Publications

1) Publication Citation Quantities: Table VII shows the yearly citation counts. In addition to the distribution of publications, a noteworthy pattern emerges. In Scopus, the annual citation count has demonstrated a decline since 2019. In contrast, within Web of Science, the annual citation count has exhibited a consistent rise since 2019. As of August 2, 2023, Scopus has documented slightly over 20 annual citations, whereas Web of Science has amassed an impressive tally exceeding 2000 annual citations.

2) Comprehensive Analysis of Highly Cited Papers: A meticulous scrutiny and assessment of the ten most highly cited papers was carried out to unravel comprehensive research methodologies. Out of these, a filtering procedure was applied to pinpoint those that specifically addressed the ensuing areas: (i) Artificial Intelligence techniques, (ii) Semiconductor domain, and (iii) Defects and Failures. As a result of this process, we identified five papers that impeccably aligned with these criteria, and their details are documented in Table VIII.

Cheon et al. [7] introduced an automatic defect classification (ADC) technique grounded in deep learning principles. This approach proficiently categorizes diverse forms of surface damage on wafers. The analysis encompassed a comprehensive dataset, comprising 2,123 images within the Dataset-TT (Train & Test) category, and an additional 30 images in the Dataset-UN (Unknown) defect class. The Convolutional Neural Network (CNN) algorithm was harnessed to process these images. The Dataset-TT consisted of 2,123 images categorized into five distinct defect classes. Impressively, the classification outcomes illustrated a remarkable accuracy of 96.0%.

Saqlain et al. [8] proposed a soft voting ensemble (SVE) classifier equipped with multi-type features, specifically for the identification of defect patterns within wafer maps. The analysis employed the WM-811K dataset, encompassing 811,457 wafer maps originating from 46,293 lots. Three distinct types

Author	Institution	Country	Publication count, n(%) Scopus (N=453)	Web of Science (N=355)
Kang, Seokho	Sungkyunkwan University	South Korea	7 (1.55)	6 (1.69)
Yu, Nai-gong	Beijing University of Technology	China	7 (1.55)	5 (1.41)
Xu, Qiao	Beijing University of Technology	China	7 (1.55)	5 (1.41)
Yu, Jianbo	Tongji University	China	7 (1.55)	7 (1.97)
Halder, Sandip	Inter-university MicroElectronics Centre	Belgium	6 (1.32)	5 (1.41)
Pahwa, Ramanpreet Singh	Institute for Infocomm Research	Singapore	6 (1.32)	2 (0.56)
López de la Rosa	Francisco, Universidad de Castilla-La Mancha	Spain	5 (1.1)	3 (0.85)
Gómez-Sirvent, José L.	Universidad de Castilla-La Mancha	Spain	5 (1.1)	5 (1.41)
Morales, Rafael	Universidad de Castilla-La Mancha	Spain	5 (1.1)	5 (1.41)
Fernández-Caballero, Antonio	Universidad de Castilla-La Mancha	Spain	5 (1.1)	5 (1.41)

TABLE VI
TOP 10 PRODUCTIVE AUTHORS.

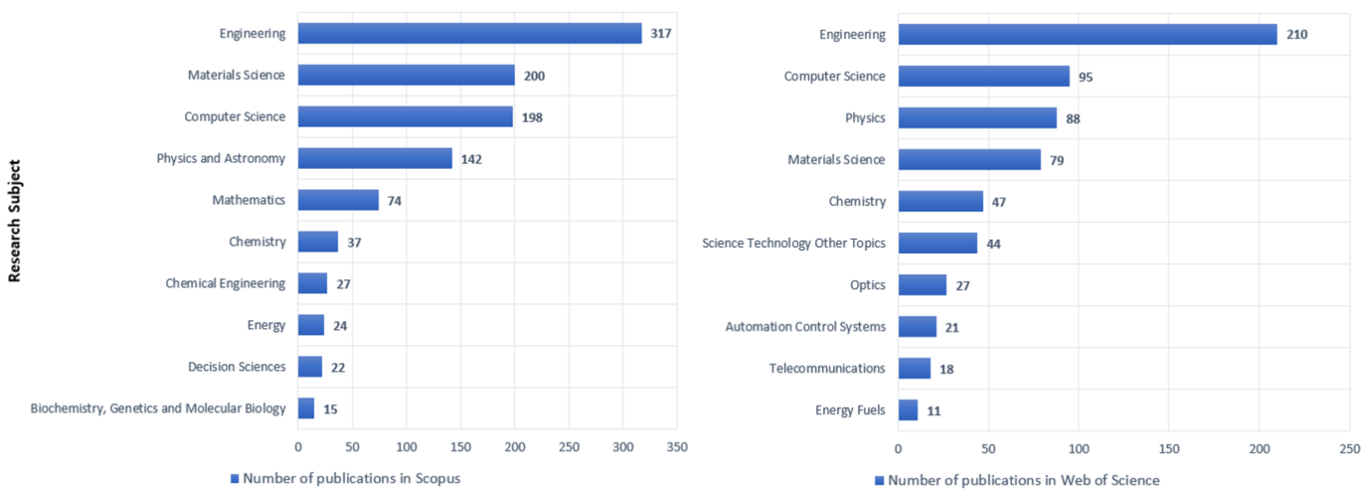

Fig. 2. Publication count of top 10 research subjects.

Year	Citation count, n Scopus	Web of Science
2019	1027	1343
2020	968	1944
2021	651	2455
2022	441	4424
2023	27	2122

TABLE VII
NUMBER OF CITATIONS PER YEAR.

of features were extracted: density-based, geometry-based, and radon-based. The study encompassed four machine learning classifiers: logistic regression (LR), random forests (RFs), gradient boosting machine (GBM), and artificial neural network (ANN). The assessment of classification outcomes included a range of performance metrics such as accuracy, precision, recall, F1 Score, and AUC score, achieving values of 95.9%, 96.9%, 96.9%, 96.7%, and 99.9%, respectively.

Wang et al. [9] presented an innovative deep learning framework termed as the adaptive balancing generative adversarial network (AdaBalGAN), specifically designed for recognizing defective patterns (DPR) within wafer maps characterized by imbalanced data. In this endeavor, the WM-811K dataset was harnessed, and three distinct feature sets were extracted: density-based, geometry-based, and radon-based features. Through experimentation, it was evident that the AdaBalGAN model, as proposed, surpassed conventional models, showcasing superior performance with an accuracy rate of 96%.

Nakazawa et al. [10]introduced deep convolutional encoder-decoder neural network architectures, specifically SegNet, U-Net, and FCN, as a means to detect and segment abnormal defect patterns within wafer maps. Their dataset encompassed 17,000 samples derived from 1,191 wafers. To augment the training process, synthetic wafer maps were generated for eight foundational defect patterns. Notably, the study demonstrated the model's capacity to detect hitherto unseen patterns exclusively through synthetic wafer maps. The experimental outcomes underscored remarkable levels of accuracy, with U-Net, SegNet, and FCN achieving impressive values of 98%, 99%, and 97%, respectively.

Saqlain et al. [11] proposed a deep learning-based approach, specifically a convolutional neural network, named CNN-WDI, tailored for the automatic identification of wafer defects. The WM-811K dataset was employed, and three

Year	Authors	Defects	Datasets	Algorithm	Features	Output	Results
2019	Sejune Cheon et al. [7]	Wafer surface defects	2,123 Dataset-TT images, 30 Dataset-UN defect images by scanning electron microscope	CNN[1]	Pixel of 160×160 image	Related to wafer surface defects	Accuracy 0.96
2019	Muhammad Saqlain et al. [8]	The defective patterns in the wafer maps	The WM-811K dataset: 811,457 wafer maps generated from 46,293 lots during circuit probe tests in a fabrication process	Soft voting ensemble classifier (LR[2], RFs[3], GBM[4], ANN[5])	Density-Based features, Geometry-Based features, Radon-Based features	Related to wafer map defect patterns	Accuracy 0.95, precision 0.96, recall 0.96, F1 0.96, AUC[6] 0.99
2019	Junliang Wang et al. [9]	The defective patterns in the wafer maps	The WM-811K dataset: 811,457 wafer maps generated from 46,293 lots during circuit probe tests in a fabrication process	Adaptive balancing generative adversarial network	Density-Based features, Geometry-Based features, Radon-Based features	Related to wafer map defect patterns	10-fold cross-validation accuracy 0.96
2019	Takeshi Nakazawa et al. [10]	The basic defective patterns and unseen defect patterns in the wafer maps	17,000 Dataset and 1,191 wafers	Deep Convolutional Encoder-Decoder Neural Network (SegNet, U-Net, FCN)	Wafer map size of 344 × 480	Related to basic defect patterns and unseen defect patterns	Accuracy 0.98, 0.99, 0.97 for U-Net, SegNet and FCN respectively
2020	Muhammad Saqlain et al. [11]	The defective patterns in the wafer maps	The WM-811K dataset: 811,457 wafer maps generated from 46,293 lots during circuit probe tests in a fabrication process	Deep learning-based convolutional neural network for automatic wafer defect identification (CNN-WDI)	Pixel of 224×224 image	Related to wafer map defect patterns	Accuracy 0.96

[1]CNN: Convolutional Neural Network
[2]LR: Logistic Regression
[3]RFs: Random Forests
[4]GBM: Gradient Boosting Machine
[5]ANN: Artificial Neural Network
[6]AUC: Area Under the Curve

TABLE VIII
SUMMARY OF RESEARCH METHODOLOGIES EMPLOYED IN HIGHLY CITED PUBLICATIONS.

distinct types of features—density-based, geometry-based, and radon-based—were extracted. To address class imbalance, a data augmentation technique was implemented. Moreover, enhancements in the classification performance of the CNN-WDI model were achieved through the incorporation of batch normalization and spatial dropout. Experimental results showcased a commendable average classification accuracy of 96.2% for the CNN-WDI model, adeptly detecting nine diverse wafer map defects.

IV. Discussion

In this study, we conducted an extensive bibliometric analysis and trend review evaluation on articles related to AI methods, which are applied to defects within the semiconductor domain from 2019 to 2023. A comprehensive analysis was conducted on a representative set of 808 papers, sourced from two prominent citation databases, namely Scopus and Web of Science.

Evidently, the escalating count of yearly publications and citations undeniably underscores the escalating intrigue and significance within this research sphere. Drawing from the publication numbers, China emerges as the most active participant, closely trailed by the United States and South Korea. In terms of institutions, the Chinese Academy of Sciences, Samsung Electronics, and Sungkyunkwan University emerged as the frontrunners. Among the various publication sources, Proceedings of SPIE (Scopus) and IEEE Transactions on Semiconductor Manufacturing (Web of Science) earned distinction as the most prolific contributors. Notably, the Keyword Co-occurrence network graph underscored the paramount utilization of artificial intelligence techniques, including deep learning, machine learning, classification, convolutional neural networks, and image enhancement. Furthermore, semiconductor-focused keywords distinctly spotlighted research primarily centered around the wafer level.

Through our conducted trend analysis review, a distinct

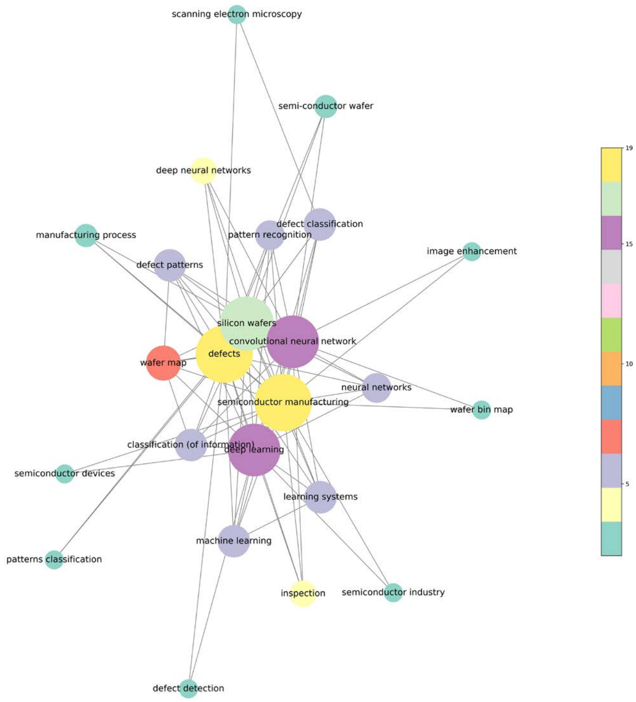

Fig. 3. Keyword co-occurrence network graph; the color map on the right side represents the degree centrality

spotlight was cast on highly cited papers, which unveiled significant research trends. A predominant theme among these papers centered around the investigation of defects in wafer maps and wafer surfaces. These analyses were facilitated by electron microscope scan images garnered from real equipment or the WM-811K dataset. In terms of methodologies, a range of algorithms including ensemble classifiers, and deep learning techniques like convolutional neural networks and generative adversarial networks were harnessed for the purpose of defect classification. Impressively, these approaches yielded remarkable performance levels, boasting an accuracy exceeding 95%.

From our research, we have distilled several key implications. Firstly, the AI applications we investigated in the context of defect analysis within semiconductor manufacturing bear significant potential for shaping future research. By effectively classifying and predicting defects through well-established case studies, AI technologies can find widespread utility and integration within the semiconductor manufacturing landscape. Secondly, given that semiconductor manufacturing is a high-production and low-defect-rate industry operating at ppm levels, the AI applications we've examined in defect analysis could serve as exemplars for other manufacturing sectors seeking to optimize their processes. Moreover, aligned with the trajectory of the Fourth Industrial Revolution and the realm of digital transformation, the advancements in AI application technologies can greatly amplify real-time decision optimization and operational flexibility. These efforts collectively contribute to the evolution of the manufacturing sector and its transition towards intelligent production paradigms.

However, our research does come with certain limitations. One substantial constraint arises from the inherent opacity in the inner workings of artificial neural networks, leading to difficulties in offering clear and comprehensible explanations for their decision-making processes. The intricate and deep network structures of these models present challenges in providing lucid insights into their judgments, ultimately obstructing their transparent comprehension and application.

Furthermore, it's noteworthy that many studies we encountered primarily focus on specific stages, particularly the wafer level, within the semiconductor manufacturing sequence. Yet, the broader spectrum of defect research across the various phases of semiconductor production, encompassing fab, package, module, and others, remains relatively underexplored. Considering the constant evolution of semiconductor manufacturing processes toward miniaturization, the adaptation of researched AI techniques to these evolving processes poses both a challenge and an opportunity warranting further exploration.

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