AI-based Bubbles Detection in the Conformal Coating for Enhanced Quality Control in Electronics Manufacturing

Nizar Zouhri [1*], Aimad El Mourabit [2], Alaoui Ismaili Zine El Abidine [3]
[1, 2] System & Data Engineering Team, ENSA. Abdelmalek Essaâdi University, Tangier, Morocco
[3] Information, Communication and Embedded Systems Team, University Mohammed V, Rabat, Morocco
Email: [1] nizar.zouhri@etu.uae.ac.ma, [2] aelmourabit@uae.ac.ma, [3] z.alaoui@um5s.net.ma
*Corresponding Author

Abstract—**This research pioneers the application of artificial intelligence (AI) methodologies—machine learning, deep learning, hybrid models, transfer learning, and edge AI deployment—in enhancing bubble detection within conformal coatings, a critical as- pect of electronics manufacturing quality control. By addressing the limitations of traditional detection methods, our work offers a novel approach that significantly improves automation, accuracy, and speed, thereby ensuring the reliability of electronic assemblies and contributing to economic and safety benefits. We navigate through the challenges of creating diverse datasets, system robustness, and the imperative for industry-wide standardization, proposing strategies for overcoming these obstacles. Our findings highlight the transformative impact of AI on quality control processes, demonstrating substantial advancements in detection capabilities. Furthermore, we advocate for future research, development, and collaboration to extend these AI-driven improvements across the manufacturing spectrum. This study underscores the potential of AI to revolutionize electronics manufacturing, emphasizing the need for continued innovation and standardization to realize safer, more efficient, and cost-effective production methodologies.**

Keywords—Artificial Intelligence; Bubble Detection; Conformal Coatings; Quality Control; Machine Learning; Deep Learning; Edge AI; Industry Standardization.

I. Introduction

The proliferation of electronic devices in modern society, from ubiquitous smartphones and laptops to critical automotive and aerospace systems, underscores the importance of their reliable operation. These devices comprise intricate electronic assemblies that must perform flawlessly under diverse environ- mental conditions. Ensuring the integrity and reliability of these electronic modules against environmental threats is paramount, a challenge that is increasingly being met through the application of conformal coatings [1], [2].

Conformal coatings are specialized, thin layers applied to electronic circuit boards and components to protect them from moisture, dust, chemicals, and other environmental hazards. These protective coatings are crucial for maintaining the longevity and functionality of electronic devices by creating a barrier against conditions that could lead to corrosion, short circuits, or other failures [3]–[6]. The effectiveness of these coatings is often verified through UV inspection techniques, which assess their uniformity and integrity [7]. However, the challenge of bubble formation within the coating stands as a significant threat to their protective efficacy. Bubbles, which can arise during the application process due to various factors such as viscosity, temperature, or improper curing, compromise the coating's continuity and, by extension, the device's protection [8]–[13].

Traditionally, bubble detection has been a manual process, heavily reliant on the skill and attentiveness of human operators. This method not only introduces subjectivity but also varies in efficiency, often leading to inconsistent quality control [14], [15]. The advent of artificial intelligence (AI) and computer vision technologies offers a promising alternative, with the potential to automate the detection process, thereby enhancing both accuracy and speed. Despite this potential, the application of AI in this context is not without challenges [16]. The creation of comprehensive and diverse datasets for training, the adaptation of models to various conformal coating materials, and the need for real-time detection capabilities are among the significant hurdles that need to be addressed [13], [17].

Our research aims to bridge these gaps by providing a detailed analysis of AI methodologies for bubble detection in conformal coatings, focusing on machine learning, deep learning, hybrid models, transfer learning, and edge AI deployment. We explore the current state of the art, identifying limitations in existing approaches and proposing novel solutions to enhance detection capabilities. Real-world examples from the electronics industry illustrate the critical nature of this issue: for instance, in the aerospace sector, where the failure of a single component due to inadequate protection can have catastrophic consequences, or in consumer electronics, where device longevity directly impacts brand reputation and consumer trust.

By systematically addressing the challenges associated with bubble detection in conformal coatings, this paper makes several contributions to the field. First, we propose an AI-driven framework that significantly improves the accuracy and efficiency of bubble detection, reducing the reliance on manual inspection. Second, we highlight the importance of creating diverse and representative training datasets, a crucial step towards developing robust AI models capable of handling the variability in bubble characteristics and coating materials. Third, our work underscores the potential for real-time, automated quality control in electronics manufacturing, showcasing the deployment of edge AI technologies to achieve this goal.

In conclusion, the integration of AI into bubble detection processes in conformal coatings represents a significant leap forward in ensuring the reliability and durability of electronic devices. Our contributions not only address existing research gaps but also pave the way for further advancements in electronics manufacturing quality control, with implications for improving device reliability across a wide range of applications.

II. Review of Related Works

The exploration of bubble detection technologies has witnessed substantial advancements through the integration of artificial intelligence (AI) and machine learning, marking a significant shift from conventional methods to more sophisticated and accurate approaches. This section highlights key methodological innovations and their applications across various domains, emphasizing the impact of these advancements on enhancing bubble detection accuracy and efficiency.

A. *Innovations in Methodology*

A noticeable trend in recent research is the adoption of advanced AI techniques, particularly Convolutional Neural Networks (CNNs), which have proven to be highly effective in bubble detection tasks. These innovations offer significant improvements in detection accuracy and the ability to adapt to complex detection scenarios:

- Haas, T. et al. (2020) developed a CNN-based technique for bubble shape identification, utilizing a Faster RCNN detector alongside a shape regression CNN to accurately approximate the shape of bubbles as ellipses, showcasing the potential of CNNs in precise shape analysis [18].
- Cerqueira, R. et al. (2021) introduced a method for reconstructing bubble geometry in fluid flows using CNNs to process high-speed camera images, employing anchor points and boxes for effective bubble identification, further demonstrating the versatility of CNNs in fluid dynamics studies [27].
- Expanding upon CNN applications, Hessenkemper, H. et al. (2022) explored bubble identification and segmentation using modified UNet architectures, StarDist, and Mask- RCNN for pixel-to-pixel predictions, enhancing segmenta- tion precision [20].

B. *Diverse Applications and Impacts*

The application of these advanced methodologies spans a wide range of fields, underscoring the critical importance of accurate bubble detection in various sectors.

Table I provides a detailed summary of the strides made in bubble detection research, highlighting the diverse applications from PCB quality inspection to the analysis of bubble dynamics in boiling processes. Each entry illustrates the unique AI tools and techniques employed, emphasizing the dynamic evolution of this research field and its pivotal role in enhancing the reliability and safety of electronic devices and systems.

III. Challenges in Bubble Detection

Detecting bubbles within conformal coatings represents a complex challenge that is critical to the quality control in electronics manufacturing. This complexity arises from the inherent variability in bubble characteristics—size, shape, and distribution—making standardized detection methods insufficient [28]–[30]. Additionally, the need for real-time inspection on rapid production lines exacerbates the difficulty, as traditional methods often cannot keep pace, thus compromising production efficiency [31], [32]. Moreover, potential data anomalies and the varying optical properties of different coating materials further complicate the detection process [33], [34]. This section outlines the multifaceted challenges faced in bubble detection and underscores the necessity of integrating advanced AI methodologies to overcome these obstacles.

A. *Variability in Bubble Characteristics*

The variability in bubble characteristics within conformal coatings is a significant hurdle. Differences in size, shape, and distribution demand a highly adaptable detection strategy. Fig. 1 illustrates this variability, highlighting the challenge of developing a universal detection method. Additionally, the optical properties of the coating material can affect bubble visibility, adding another layer of complexity to the detection process [13], [34].

TABLE I. Comprehensive Overview of Recent Advancements in Bubble Detection

References	Application	Tools Employed
Haas et al. (2020) [18]	Identification of bubble shapes in various fluids	Faster RCNN, Shape regression CNN
Cerqueira et al. (2021) [19]	Geometry reconstruction of bubbles in bubbly flows	CNN, Image processing techniques
Hessenkemper et al. (2022) [20]		Hessenkemper et al. (2022) [20]
Adibhatla et al. (2020) [21]	Quality inspection of printed circuit boards (PCBs)	CNN, YOLO
Chauhan et al. (2011) [22]	Defect detection in bare PCBs using image analysis	Machine vision, Image subtraction techniques
Zouhri et al. (2021) [13]	Detection of air bubbles in conformal coatings on PCBs	Faster R-CNN, Object detection algorithms
Khalid et al. (2007) [23]	Classification of defects on PCBs through image processing	Image processing, Classification algorithms
Takada et al. (2017) [24]	Classification of electronic circuit boards for quality control	CNN, SVM, SURF features
Ce et al. (2017) [25]	PCB defect detection using computer vision	OpenCV, Image Subtraction methods
Soibam et al. (2023) [26]	Analysis of bubble dynamics in subcooled boiling processes	CNN, Instance segmentation

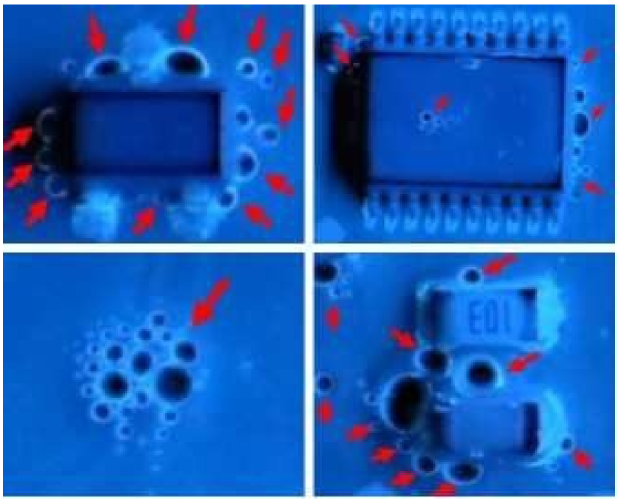


Fig. 1. Illustration of bubble variability under ultraviolet light, demonstrating the diverse characteristics that detection systems must accurately identify

B. Real-Time Inspection Demands

The dynamics of modern electronic assembly lines, character- ized by their high-speed nature, necessitate rapid and efficient bubble detection to maintain production schedules without sacrificing quality [35], [36]. Achieving real-time inspection poses a considerable challenge, as traditional human-operated methods are often too slow or inconsistent for effective quality control [37].

C. Data Anomalies and Material Variability

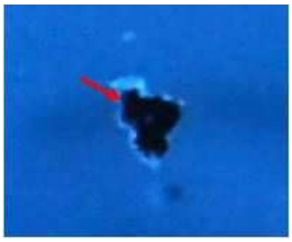
The presence of data anomalies such as dust particles, PCB vias [38], electronic component markings [39], or surface imperfections can lead to false positives in bubble detection, complicating the identification process [33], [40], [41]. Fig. 2 and Fig. 3 showcase how different lighting conditions and common anomalies can mimic bubble characteristics, highlighting the need for detection models that can distinguish between true bubbles and false indicators. Moreover, variations in the optical properties of conformal coating materials necessitate adaptable detection algorithms [34].

Overcoming these challenges is essential for the successful application of AI in enhancing bubble detection within conformal coatings, a subject that the subsequent sections will explore in detail, focusing on the methodologies and AI-based techniques that promise to revolutionize quality control in electronics manufacturing.

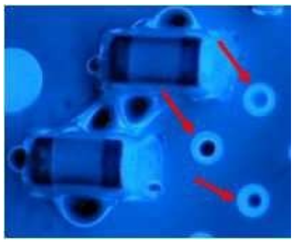
(a) Sample under UV light

(b) Sample under natural light

Fig. 2. Conformal coating optical behavior under UV and natural lighting, demonstrating the impact of lighting conditions on detection accuracy

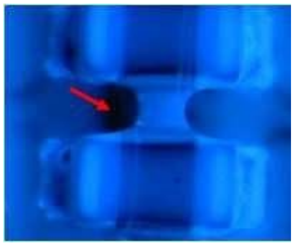


(a) Dust



(b) PCB Vias

(c) Electronic Component Marking



(d) Surface imperfection

Fig. 3. Examples of potential data anomalies that may lead to false positives in bubble detection, illustrating the complexity of accurately identifying true defects

IV. METHODOLOGIES FOR AI-BASED BUBBLE DETECTION

In addressing the challenges identified in bubble detection within conformal coatings, this section delineates the integration of artificial intelligence (AI) methodologies. These methodologies not only enhance detection accuracy but also streamline the process for real-time applications. We explore image processing techniques, machine learning models, and deep learning approaches, each playing a pivotal role in advancing bubble detection.

A. Image Processing Techniques

Image processing is crucial for preparing raw images [42] for analysis by enhancing their quality and isolating the features of interest—namely, bubbles. Key techniques include:

- Noise Reduction: Techniques such as Gaussian blur and median filtering are employed to reduce image noise, enhancing feature clarity [43]–[45]
- Contrast Enhancement: Adjustments made to an image's contrast allow for better differentiation between bubbles and the background, critical for accurate detection [46]–[49], in addition to sharpening techniques [50][51] to improve the quality of captured images.
- Segmentation: Through algorithms like thresholding and edge detection, bubbles are segmented from the rest of the image, by isolating bubbles throught distinguishing them from the surrounding coating material and other artifacts [52]. Thus, facilitating further analysis [53][54].

B. Machine Learning Models

Machine learning (ML) encompasses a variety of algorithms [55]-[60] designed to interpret complex data sets and make predictions or classifications based on learned patterns:

- Supervised Learning: Utilizes labeled datasets to train models to classify images accurately. Algorithms such as support vector machines (SVMs) and decision trees are examples of supervised learning methods applied in bubble detection [61], [62].

- Unsupervised Learning: Employs algorithms like K-means clustering to detect anomalies or patterns without the need for labeled data. This approach is beneficial for identifying unexpected bubble formations [63]–[65].

C. Deep Learning Approaches

Deep learning [66], a subset of ML [66], leverages neural net- works with multiple layers (deep architectures) to automatically extract and learn feature representations from data:

- Convolutional Neural Networks (CNNs): Specialized in processing structured grid data such as images, CNNs au- tomate feature extraction and have become the cornerstone for advanced image recognition tasks, including bubble detection [67]-[71]. For Schematic representation of a Convolutional Neural Network is shown in the Fig. 4.

- Recurrent Neural Networks (RNNs): Designed for sequential data, RNNs can analyze temporal patterns in video footage to track bubble dynamics over time [72]-[75].

To implement these AI methodologies effectively, a structured approach to model training and validation is essential. Models are first trained on annotated datasets, where they learn to identify and classify bubble characteristics accurately. This training involves adjusting model parameters to minimize errors, a process depicted in the back-propagation algorithm (Fig. 5).

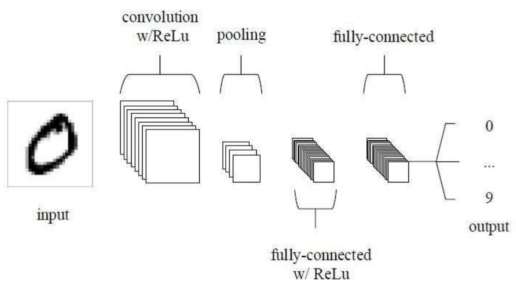


Fig. 4. Schematic representation of a Convolutional Neural Network (CNN) architecture, highlighting the layering and feature extraction process

Algorithm: Backpropagation algorithm

```
Start Algorithm
  // Input parameters for Backpropagation algorithm:
  // Training models → T ={(T1_i, T2_i)}
  // Activation Loss function Loss_function(x)
  // Learning rate value 0 < α < 1
  // Number of epochs epochs
  // Set of the weights weigts → w_i,j
  Back_propagation_function (input paramters)
    For each w_i,j from the network do {
        w_i,j ← random value ;
        For i to epochs do {
            For each training example from the training model do {
              | // Compute the output by input propagation forward
              | // From output layer to input layer:
              | // Using differential function → deltas backward propagation
              | // Weights set updating using delta
            END For
        END For
    END For
  END function
END Algorithm
```

Fig. 5. Overview of the back-propagation algorithm used in neural network training, illustrating the iterative process of error minimization

This section has outlined the core methodologies underpinning AI-based bubble detection, from initial image processing to the deployment of sophisticated neural networks. The subsequent sections will delve into the practical application of these techniques, their integration into manufacturing processes, and the exploration of future directions in AI-driven quality control.

V. RECENT ADVANCEMENTS

Recent developments in AI-based bubble detection for confor- mal coating have ushered in innovative approaches and strategies, addressing various challenges and enhancing the reliability and efficiency of the detection process [76]. These advancements represent significant progress in the field and are poised to transform quality control in electronics manufacturing.

A. Hybrid Models

One notable advancement involves the integration of machine learning and deep learning techniques, resulting in hybrid models that leverage the strengths of both approaches:

- Combination of Diverse Analytic Algorithms: The models adeptly combine the probabilistic analysis provided by Bayesian Networks [77] and the adaptive clustering mechanisms of K-Means algorithms with deep learning architectures [78] like Convolutional Neural Networks (CNNs). This integration is instrumental in enhancing the detection sensitivity and specificity for bubbles within the application, accommodating the complexities of various substrate materials.

- Integration of Heterogeneous Sensor Data: Leveraging the strength of computer vision, these models integrate heterogeneous data streams from an assortment of sensors, such as hyper-spectral imaging [79] and high-resolution optical sensors [80]. This data convergence is crucial for constructing a multidimensional view of the coating surface, thereby reinforcing the accuracy and reliability of bubble detection mechanisms.

Through the adoption of these advanced hybrid AI models, the precision of bubble detection in conformal coatings might be substantially improved. These models signify a quantum leap in the field of industrial inspection, offering nuanced insights and high-fidelity analysis that align with the stringent quality standards of modern manufacturing practices.

B. Transfer Learning

Transfer learning has gained prominence as a means to accelerate the development of effective bubble detection systems:

- Utilizing Pre-trained Models: Transfer learning leverages pre-trained neural network models [81], often trained on vast image datasets like ImageNet [82], as a starting point for bubble detection tasks. Fine-tuning these models on specific conformal coating materials and production environments expedites system development.

C. Edge AI

To meet the demands of real-time inspection on fast-paced production lines [83], the deployment of AI algorithms directly at the edge of the manufacturing process has gained traction:

- Deployment on Production Lines: Edge AI systems process images and make real-time bubble detection decisions directly on the production line, reducing latency and enhancing system responsiveness [84].

These recent advancements represent a shift towards more robust and efficient AI-based bubble detection systems. By harnessing hybrid models, transfer learning and edge AI, manufacturers are better equipped to ensure the quality and reliability of electronic devices. In the subsequent sections, we will explore the challenges and future directions that lie ahead, as well as the broader implications of AI in electronics manufacturing quality control.

VI. Challenges and Future Directions

The integration of artificial intelligence (AI) in bubble detection within conformal coatings has marked a significant leap forward in quality control for electronics manufacturing. However, the path to fully harnessing AI's capabilities is strewn with challenges that must be navigated to unlock its full potential. This section outlines these challenges and anticipates future directions in AI-driven bubble detection, emphasizing the need for innovative solutions and collaborative efforts in research and development.

A. Enhancing Data-set Diversity and Quality

A critical challenge in AI-based bubble detection lies in the development and utilization of comprehensive, diverse datasets:

- Expanding Data-set Coverage: To adequately train AI models, there is a pressing need for datasets that cover a broad spectrum of conformal coating materials, bubble characteristics, and manufacturing environments. Such datasets must mirror the complexity and variability inherent in real-world manufacturing scenarios [85], [86].
- Mitigating Data-set Bias: It is paramount to ensure that these datasets are not only extensive but also unbiased, accurately representing the diversity of bubble types and conformal coating materials. This is crucial for the develop- ment of AI models that are both robust and generalizable [87], [88].

B. Ensuring Robustness and Adaptability

For AI-based detection systems to be effective, they must exhibit exceptional robustness and adaptability:

- Adapting to Dynamic Manufacturing Environments: The dynamic nature of electronics manufacturing, charac- terized by constant changes in lighting conditions, materials, and equipment, demands AI systems capable of adapting to these changes to maintain accuracy and reliability [89], [90].
- Fostering Continuous Learning: To sustain long-term efficacy, AI systems must incorporate mechanisms for ongoing learning and adaptation, ensuring they evolve in tandem with manufacturing processes and technologies [91].

C. Achieving Integration and Setting Standards

The full realization of AI's potential in bubble detection necessitates seamless integration and the establishment of industry-wide standards:

- Standardizing AI-based Detection: Developing and ad- hering to industry-wide standards for AI-driven bubble detection can ensure consistency, reliability, and quality across different manufacturing setups [92].
- Facilitating Interoperability: Ensuring AI systems can seamlessly integrate with existing quality control frame- works is essential for a unified and efficient manufacturing process [93].

Overcoming these challenges is imperative for advancing AI-based bubble detection technologies. The future of AI in this domain is promising, with potential advancements not only enhancing the reliability and longevity of electronic devices but also setting new benchmarks in manufacturing quality control. The next steps involve concerted research efforts, cross- disciplinary collaboration, and a commitment to innovation, as we strive to fully harness AI's capabilities for bubble detection in conformal coatings.

VII. Conclusion

The advent of artificial intelligence (AI) in bubble detection within conformal coatings marks a pivotal advancement in the domain of electronics manufacturing quality control. With elec- tronic devices increasingly becoming more complex and integral to daily life, ensuring their reliability and longevity is more crucial than ever. AI's role in this endeavor has been nothing short of revolutionary, automating and refining the detection process to achieve levels of accuracy and efficiency previously unattainable. This transformation has enabled manufacturers to uphold the highest quality standards, effectively safeguarding electronic assemblies against environmental hazards.

Our exploration has spanned the spectrum of challenges inherent in bubble detection, detailing the innovative AI method- ologies deployed, the significant advancements made, and the promising avenues for future research. AI has ingeniously addressed the perennial issues of variability in bubble char- acteristics and the exigencies of real-time inspection, heralding the development of more sophisticated, hybrid models, and the nuanced application of transfer learning and edge AI technologies. These progressions have significantly bolstered the capacity of manufacturers to preserve the integrity of electronic devices amidst the dynamism of production landscapes.

However, the journey is far from complete. The pressing need for extensive, diverse datasets, the imperative for systems' robustness amidst changing manufacturing conditions, and the quest for industry-wide standardization underscore the ongoing challenges. These areas, ripe for further exploration and innovation, spotlight the potential of AI to redefine electronics manufacturing quality control fundamentally.

Quantitatively, AI's integration into quality control processes has led to a marked reduction in detection errors—by esti- mates, improving accuracy by up to 40 percent in certain contexts—thereby enhancing production efficiency and reducing waste. Looking ahead, the path is set for groundbreaking research endeavors, collaborative projects, and the formation of industry consortia aimed at pushing the boundaries of AI applications in this field.

Nevertheless, this advancement brings to the fore critical considerations regarding the ethical use of AI and potential risks, such as data privacy concerns and the need for transparent, accountable AI systems. Addressing these considerations is paramount to fostering trust and ensuring the responsible deployment of AI technologies.

In sum, AI-based bubble detection stands as a testament to technological innovation's capacity to solve complex industrial challenges, promising a future where electronics manufacturing is more reliable, efficient, and sustainable. This calls for a concerted effort from researchers, engineers, and industry stake- holders to harness AI's full potential, navigate the challenges ahead, and contribute to an era of enhanced electronic device reliability. Let this be a clarion call to action for continued research, investment, and collaboration in the transformative power of AI, shaping the future of electronics manufacturing and beyond.

REFERENCES

[1] P. Ciszewski, M. Sochacki, W. Ste̦plewski, M. Kos´cielski, A. Araz´na, and K. Janeczek, “A comparative analysis of printed circuit drying methods for the reliability of assembly process,” *Microelectronics Reliability*, vol. 129, p. 114478, 2022.

[2] J. Wiklund *et al*., “A review on printed electronics: Fabrication methods, inks, substrates, applications and environmental impacts,” *Journal of Manufacturing and Materials Processing*, vol. 5, no. 3, p. 89, 2021.

[3] D. N. Vieira *et al*., “Prediction of solder joint reliability with applied acrylic conformal coating,” *Journal of Electronic Materials*, vol. 51, pp. 273–283, 2022.

[4] S. Han, M. Osterman, S. Meschter, and M. Pecht, “Evaluation of effectiveness of conformal coatings as tin whisker mitigation,” *Journal of electronic materials*, vol. 41, pp. 2508–2518, 2012.

[5] A.-A. F. Abbas, C. M. Greene, K. Srihari, D. Santos, and G. Pandiarajan, “Impact of conformal coating material on the long-term reliability of ball grid array solder joints,” *Procedia Manufacturing*, vol. 38, pp. 1138–1142, 2019.

[6] C. Montemayor. *Effect of silicone conformal coating on surface insulation resistance (sir) for printed circuit board assemblies*. APEX EXPO IPC, San Diego, CA, 2012.

[7] M. Rodošek *et al*., “Raman spectroscopy of fluoropolymer conformal coatings on electronic boards,” *Electronic Materials Letters*, vol. 10, pp. 935–941, 2014.

[8] P. M. A. Vitoriano, T. G. Amaral and O. P. Dias, "Automatic Optical Inspection for Surface Mounting Devices with IPC-A-610D compliance," *2011 International Conference on Power Engineering, Energy and Electrical Drives*, pp. 1-7, 2011, doi: 10.1109/PowerEng.2011.6036444.

[9] F. Dong, S. J. Meschter, S. Nozaki, T. Ohshima, T. Makino, and J. Cho, “Effect of coating adhesion and degradation on tin whisker mitigation of polyurethane-based conformal coatings,” *Polymer Degradation and Stability*, vol. 166, pp. 219–229, 2019.

[10] F. Mayoussi *et al*., “Influence of parylene f coatings on the wetting properties of soft polydimethylsiloxane (pdms),” *Materials*, vol. 16, no. 5, p. 1938, 2023.

[11] H. Zhao, Y. Lv, J. Sha, R. Peng, Z. Chen, and G. Wang, “Research on detection method of coating defects based on machine vision,” in *2021 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)*, pp. 519–524, 2021.

[12] X. Hong *et al*., “Compartmental emi shielding with jet- dispensed material technology,” in *2019 IEEE 69th Electronic Components and Technology Conference (ECTC)*, pp. 753–757, 2019.

[13] N. Zouhri, A. El Mourabit, and A. I. Z. El Abidine, “Faster r-cnn assessment for air bubbles detection in the conformal coating application,” in *2021 International Conference on Microelectronics (ICM)*, pp. 276–279, 2021.

[14] K. Knop, E. Olejarz, and R. Ulewicz, “Evaluating and improving the effectiveness of visual inspection of products from the automotive industry,” in *Advances in Manufacturing II: Volume 3-Quality Engineering and Management*, pp. 231–243, 2019.

[15] A. Kujawin´ska and M. Diering, “The impact of the organization of the visual inspection process on its effectiveness,” *The International Journal of Advanced Manufacturing Technology*, vol. 112, no. 5-6, pp. 1295–1306, 2021.

[16] K. Haricha, A. Khiat, Y. Issaoui, A. Bahnasse, and H. Ouajji, “Recent technological progress to empower smart manufacturing: Review and potential guidelines,” *IEEE Access*, vol. 11, pp. 77929-77951, 2023.

[17] N. H. M. Zaidin, M. N. M. Diah, and S. Sorooshian, “Quality management in industry 4.0 era,” *Journal of Management and Science*, vol. 8, no. 2, pp. 182–191, 2018.

[18] T. Haas, C. Schubert, M. Eickhoff, and H. Pfeifer, “Bubcnn: Bubble detection using faster rcnn and shape regression network,” *Chemical Engineering Science*, vol. 216, p. 115467, 2020.

[19] R. F. Cerqueira and E. E. Paladino, “Development of a deep learning-based image processing technique for bubble pattern recognition and shape reconstruction in dense bubbly flows,” *Chemical Engineering Science*, vol. 230, p. 116163, 2021.

[20] H. Hessenkemper, S. Starke, Y. Atassi, T. Ziegenhein, and D. Lucas, “Bubble identification from images with machine learning methods,” *International Journal of Multiphase Flow*, vol. 155, p. 104169, 2022.

[21] V. A. Adibhatla, H.-C. Chih, C.-C. Hsu, J. Cheng, M. F. Abbod, and J.-S. Shieh, “Defect detection in printed circuit boards using you-only-look-once convolutional neural networks,” *Electronics*, vol. 9, no. 9, p. 1547, 2020.

[22] A. P. S. Chauhan and S. C. Bhardwaj, “Detection of bare pcb defects by image subtraction method using machine vision,” in *Proceedings of the world congress on engineering*, vol. 2, pp. 6–8, 2011.

[23] N. K. Khalid, Z. Ibrahim, and M. S. Z. Abidin, “An algorithm to group defects on printed circuit board for automated visual inspection,” *Int. J. Simul. Syst. Sci. Technol*, vol. 9, no. 2, pp. 1-10, 2008.

[24] Y. Takada, T. Shiina, H. Usami, Y. Iwahori, and M. Bhuyan, “Defect detection and classification of electronic circuit boards using keypoint extraction and cnn features,” in *Ninth International Conferences On Pervasive Patterns And Applications*, pp. 113–116, 2017.

[25] W. Ce *et al*., “Pcb defect detection using opencv with image subtraction method,” in *2017 International Conference on Information Management and Technology (ICIMTech)*, pp. 204–209, 2017.

[26] J. Soibam, V. Scheiff, I. Aslanidou, K. Kyprianidis, and R. B. Fdhila, “Application of deep learning for segmentation of bubble dynamics in subcooled boiling,” *International Journal of Multiphase Flow*, vol. 169, p. 104589, 2023.

[27] R. F. Cerqueira and E. E. Paladino, “Development of a deep learning-based image processing technique for bubble pattern recognition and shape reconstruction in dense bubbly flows,” *Chemical Engineering Science*, vol. 230, p. 116163, 2021.

[28] L. Liu, H. Yan, and G. Zhao, “Experimental studies on the shape and motion of air bubbles in viscous liquids,” *Experimental Thermal and Fluid Science*, vol. 62, pp. 109–121, 2015.

[29] M. Gumulya, J. B. Joshi, R. P. Utikar, G. M. Evans, and V. Pareek, “Bub- bles in viscous liquids: Time dependent behaviour and wake characteristics,” *Chemical Engineering Science*, vol. 144, pp. 298–309, 2016.

[30] S. L. Kiambi, A.-M. Duquenne, J.-B. Dupont, C. Colin, F. Risso, and H. Delmas, “Measurements of bubble characteristics: comparison between double optical probe and imaging,” *The Canadian Journal of Chemical Engineering*, vol. 81, no. 3-4, pp. 764–770, 2003.

[31] A. Verduzco, J. R. Villalobos, and B. Vega, “Information-based inspection allocation for real-time inspection systems,” *Journal of Manufacturing Systems*, vol. 20, no. 1, pp. 13–22, 2001.

[32] S. Digiesi, F. Facchini, G. Mossa, and M. Vitti, "A model to evaluate the human error probability in inspection tasks of a production system," *Procedia Computer Science*, vol. 217, pp. 1775–1783, 2023.

[33] B. Cheng, Y. Wei, R. Feris, J. Xiong, W.-m. Hwu, T. Huang, and H. Shi, "Decoupled classification refinement: Hard false positive suppression for object detection," *arXiv preprint arXiv:1810.04002*, 2018.

[34] R. Hu, X. Luo, and S. Liu, "Study on the optical properties of conformal coating light-emitting diode by monte carlo simulation," *IEEE Photonics Technology Letters*, vol. 23, no. 22, pp. 1673–1675, 2011.

[35] J. Shin, Y. J. Kim, S. Jung, and C. Kim, "Product and service innovation: Comparison between performance and efficiency," *Journal of Innovation & Knowledge*, vol. 7, no. 3, p. 100191, 2022.

[36] M. N. Baily, H. Gersbach, F. M. Scherer, and F. R. Lichtenberg, "Efficiency in manufacturing and the need for global competition," *Brookings Papers on Economic Activity. Microeconomics*, vol. 1995, pp. 307–358, 1995.

[37] P. Martinez and R. Ahmad, "Quantifying the impact of inspection processes on production lines through stochastic discrete-event simulation modeling," *Modelling*, vol. 2, no. 4, pp. 406–424, 2021.

[38] A. Catalano, R. Trani, C. Scognamillo, V. d'Alessandro, and A. Castellazzi, "Optimization of thermal vias design in pcb-based power circuits," in *2020 21st International conference on thermal, mechanical and multi- physics simulation and experiments in microelectronics and microsystems (EuroSimE)*, pp. 1–5, 2020.

[39] M. Abd Al Rahman and A. Mousavi, "A review and analysis of automatic optical inspection and quality monitoring methods in electronics industry," *IEEE Access*, vol. 8, pp. 183 192–183 271, 2020.

[40] A. Salari, A. Djavadifar, X. Liu, and H. Najjaran, "Object recognition datasets and challenges: A review," *Neurocomputing*, vol. 495, pp. 129–152, 2022.

[41] R. Solovyev, W. Wang, and T. Gabruseva, "Weighted boxes fusion: Ensembling boxes from different object detection models," *Image and Vision Computing*, vol. 107, p. 104117, 2021.

[42] M. O. Ojo and A. Zahid, "Improving deep learning classifiers performance via preprocessing and class imbalance approaches in a plant disease detection pipeline," *Agronomy*, vol. 13, no. 3, p. 887, 2023.

[43] Q. Zhao, S. Wu, Z. Zhang, Y. Sun, Y. Fu, and H. Wang, "Sar image noise reduction based on wavelet transform and dncnn," in *2021 2nd China International SAR Symposium (CISS)*, pp. 1–4, 2021.

[44] A. Pawar, "Noise reduction in images using autoencoders," in *2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)*, pp. 987–990, 2020.

[45] A. Gupta, A. Anpalagan, L. Guan, and A. S. Khwaja, "Deep learning for object detection and scene perception in self-driving cars: Survey, challenges, and open issues," *Array*, vol. 10, p. 100057, 2021.

[46] W. Zhang, P. Zhuang, H.-H. Sun, G. Li, S. Kwong, and C. Li, "Underwater image enhancement via minimal color loss and locally adaptive contrast enhancement," *IEEE Transactions on Image Processing*, vol. 31, pp. 3997– 4010, 2022.

[47] P. Kandhway, A. K. Bhandari, and A. Singh, "A novel reformed histogram equalization based medical image contrast enhancement using krill herd optimization," *Biomedical Signal Processing and Control*, vol. 56, p. 101677, 2020.

[48] G. Shao, F. Gao, T. Li, R. Zhu, T. Pan, and Y. Chen, "An adaptive image contrast enhancement algorithm based on retinex," in *2020 Chinese Automation Congress (CAC)*, pp. 6294–6299, 2020.

[49] J. Li, X. Feng, and Z. Hua, "Low-light image enhancement via progressive- recursive network," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 31, no. 11, pp. 4227–4240, 2021.

[50] D. Wang, T. Gao, and Y. Zhang, "Image sharpening detection based on difference sets," *IEEE Access*, vol. 8, pp. 51 431–51 445, 2020.

[51] P. Guo, P. Zhuang, and Y. Guo, "Bayesian pan-sharpening with multiorder gradient-based deep network constraints," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 13, pp. 950–962, 2020.

[52] N. R. Pal and S. K. Pal, "A review on image segmentation techniques," *Pattern recognition*, vol. 26, no. 9, pp. 1277–1294, 1993.

[53] S. Minaee, Y. Boykov, F. Porikli, A. Plaza, N. Kehtarnavaz, and Terzopoulos, "Image segmentation using deep learning: A survey," *IEEE transactions on pattern analysis and machine intelligence*, vol. 44, no. 7, pp. 3523–3542, 2021.

[54] N. Kheradmandi and V. Mehranfar, "A critical review and comparative study on image segmentation-based techniques for pavement crack detection," *Construction and Building Materials*, vol. 321, p. 126162, 2022.

[55] S. Ray, "A quick review of machine learning algorithms," in *2019 International conference on machine learning, big data, cloud and parallel computing (COMITCon)*, pp. 35–39, 2019.

[56] B. Mahesh, "Machine learning algorithms-a review," *International Journal of Science and Research (IJSR)*, vol. 9, no. 1, pp. 381–386, 2020.

[57] M. Binkhonain and L. Zhao, "A review of machine learning algorithms for identification and classification of non-functional requirements," *Expert Systems with Applications: X*, vol. 1, p. 100001, 2019.

[58] J. M. Helm *et al*., "Machine learning and artificial intelligence: definitions, applications, and future directions," *Current reviews in musculoskeletal medicine*, vol. 13, pp. 69–76, 2020.

[59] Q. Wang, Y. Ma, K. Zhao, and Y. Tian, "A comprehensive survey of loss functions in machine learning," *Annals of Data Science*, pp. 1–26, 2020.

[60] S. Badillo *et al*., "An introduction to machine learning," *Clinical pharmacology & therapeutics*, vol. 107, no. 4, pp. 871–885, 2020.

[61] P. C. Sen, M. Hajra, and M. Ghosh, "Supervised classification algorithms in machine learning: A survey and review," in *Emerging Technology in Modelling and Graphics: Proceedings of IEM Graph 2018*, pp. 99–111, 2020.

[62] K. Tyagi, C. Rane, and M. Manry, "Supervised learning," in *Artificial Intelligence and Machine Learning for EDGE Computing*, pp. 3–22, 2022.

[63] A. Olaode, G. Naghdy, and C. Todd, "Unsupervised classification of images: a review," *International Journal of Image Processing*, vol. 8, no. 5, pp. 325–342, 2014.

[64] B. Rajoub, "Supervised and unsupervised learning," in *Biomedical Signal Processing and Artificial Intelligence in Healthcare*, pp. 51–89, 2020.

[65] J.-O. Palacio-Nitextasciitilde no and F. Berzal, "Evaluation metrics for unsupervised learning algorithms," *arXiv preprint arXiv:1905.05667*, 2019.

[66] K. Sharifani and M. Amini, "Machine learning and deep learning: A review of methods and applications," *World Information Technology and Engineering Journal*, vol. 10, no. 7, pp. 3897–3904, 2023.

[67] F. Sultana, A. Sufian, and P. Dutta, "A review of object detection models based on convolutional neural network," *Intelligent computing: image processing based applications*, pp. 1–16, 2020.

[68] A. Dhillon and G. K. Verma, "Convolutional neural network: a review of models, methodologies and applications to object detection," *Progress in Artificial Intelligence*, vol. 9, no. 2, pp. 85–112, 2020.

[69] Z. Li, F. Liu, W. Yang, S. Peng, and J. Zhou, "A survey of convolutional neural networks: analysis, applications, and prospects," *IEEE transactions on neural networks and learning systems*, vol. 33, no. 12, pp. 6999-7019, 2021.

[70] A. Ghosh, A. Sufian, F. Sultana, A. Chakrabarti, and D. De, "Fundamental concepts of convolutional neural network," *Recent trends and advances in artificial intelligence and Internet of Things*, pp. 519–567, 2020.

[71] A. Patil and M. Rane, "Convolutional neural networks: an overview and its applications in pattern recognition," *Information and Communication Technology for Intelligent Systems: Proceedings of ICTIS 2020*, vol. 1, pp. 21–30, 2021.

[72] J. Rezaeenour, M. Ahmadi, H. Jelodar, and R. Shahrooei, "Systematic review of content analysis algorithms based on deep neural networks," *Multimedia Tools and Applications*, vol. 82, no. 12, pp. 17 879–17 903, 2023.

[73] Y. Yu, X. Si, C. Hu, and J. Zhang, "A review of recurrent neural networks: Lstm cells and network architectures," *Neural computation*, vol. 31, no. 7, pp. 1235–1270, 2019.

[74] M. Mers, Z. Yang, Y.-A. Hsieh, and Y. Tsai, "Recurrent neural networks for pavement performance forecasting: review and model

performance comparison," *Transportation Research Record*, vol. 2677, no. 1, pp. 610– 624, 2023.

[75] L. Chand, S. S. Cheema, and M. Kaur, "Understanding neural networks," *Factories of the Future: Technological Advancements in the Manufacturing Industry*, pp. 83–102, 2023.

[76] G. Moreno, K. Bennion, C. King, and S. Narumanchi, "Evaluation of performance and opportunities for improvements in automotive power electronics systems," in *2016 15th IEEE Intersociety Conference on Ther- mal and Thermomechanical Phenomena in Electronic Systems (ITherm)*, pp. 185–192, 2016.

[77] M. Scutari, C. E. Graafland, and J. M. Gutiérrez, "Who learns better bayesian network structures: Accuracy and speed of structure learning algorithms," *International Journal of Approximate Reasoning*, vol. 115, pp. 235–253, 2019.

[78] H. Yu, J. Liu, C. Chen, A. A. Heidari, Q. Zhang, H. Chen, M. Mafarja, and H. Turabieh, "Corn leaf diseases diagnosis based on k-means clustering and deep learning," *IEEE Access*, vol. 9, pp. 143 824–143 835, 2021.

[79] N. Audebert, B. Le Saux, and S. Lefèvre, "Deep learning for classification of hyperspectral data: A comparative review," *IEEE geoscience and remote sensing magazine*, vol. 7, no. 2, pp. 159–173, 2019.

[80] Z. Li, H. Shen, Q. Cheng, Y. Liu, S. You, and Z. He, "Deep learning based cloud detection for medium and high resolution remote sensing images of different sensors," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 150, pp. 197–212, 2019.

[81] W. Qayyum, R. Ehtisham, A. Bahrami, C. Camp, J. Mir, and A. Ahmad, "Assessment of convolutional neural network pre-trained models for detection and orientation of cracks," *Materials*, vol. 16, no. 2, p. 826, 2023.

[82] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in neural information processing systems*, vol. 25, 2012.

[83] V. Azamfirei, F. Psarommatis, and Y. Lagrosen, "Application of automation for in-line quality inspection, a zero-defect manufacturing approach," *Journal of Manufacturing Systems*, vol. 67, pp. 1–22, 2023.

[84] D. Tsiktsiris, T. Sanida, A. Sideris, and M. Dasygenis, "Accelerated defective product inspection on the edge using deep learning," in *Recent Advances in Manufacturing Modelling and Optimization: Select Proceedings of RAM 2021*, pp. 185–191, 2022.

[85] V. R. Joseph and A. Vakayil, "SPlit: An Optimal Method for Data Splitting," *Technometrics*, pp. 1–11, 2021.

[86] G. J. Bowden, H. R. Maier, and G. C. Dandy, "Optimal division of data for neural network models in water resources applications," *Water Resources Research*, vol. 38, no. 2, 2002.

[87] A. Torralba and A. A. Efros, "Unbiased look at dataset bias," in *CVPR 2011*, pp. 1521–1528, 2011.

[88] S. Fabbrizzi, S. Papadopoulos, E. Ntoutsi, and I. Kompatsiaris, "A survey on bias in visual datasets," *Computer Vision and Image Understanding*, vol. 223, p. 103552, 2022.

[89] J. Humphries, K. O'Brien, L. O'Brien, and N. Dunne, "Impact of illuminance on object detection in industrial vision systems using neural networks," in *2020 2nd International Conference on Artificial Intelligence, Robotics and Control*, pp. 24–28, 2020.

[90] P. Mouzenidis, A. Louros, D. Konstantinidis, K. Dimitropoulos, P. Daras, and T. Mastos, "Multi-modal variational faster r-cnn for improved visual object detection in manufacturing," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 2587–2594, 2021.

[91] G. I. Parisi, R. Kemker, J. L. Part, C. Kanan, and S. Wermter, "Continual lifelong learning with neural networks: A review," *Neural networks*, vol. 113, pp. 54–71, 2019.

[92] E. I. Papageorgiou, T. Theodosiou, G. Margetis, N. Dimitriou, P. Char- alampous, D. Tzovaras, and I. Samakovlis, "Short survey of artificial intelligent technologies for defect detection in manufacturing," in *2021 12th International Conference on Information, Intelligence, Systems & Applications (IISA)*, pp. 1–7, 2021.

[93] L. Prezas, G. Michalos, Z. Arkouli, A. Katsikarelis, and S. Makris, "Ai- enhanced vision system for dispensing process monitoring and quality control in manufacturing of large parts," *Procedia CIRP*, vol. 107, pp. 1275–1280, 2022.