A Survey on 3D Anomaly Synthesis and Defect Detection in Industrial Inspection

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Abstract

This survey paper explores the advanced techniques of anomaly synthesis and defect detection in industrial inspection, emphasizing their critical role in enhancing quality control processes. The integration of synthetic anomalies, generated through methods such as Generative Adversarial Networks (GANs) and Neural Radiance Fields (NeRF), has significantly improved the training and accuracy of defect detection models. These techniques address challenges like data scarcity and class imbalance, crucial for environments with complex manufacturing processes. Machine learning, particularly deep learning models, has revolutionized defect detection by augmenting traditional methods and enhancing precision in detecting rare and complex anomalies. The survey highlights the application of these techniques across various industries, including manufacturing, automotive, and electronics, demonstrating their transformative impact on operational efficiency and product quality. Despite advancements, challenges remain in data quality, model generalization, and computational efficiency. Future directions include refining synthetic anomaly generation, enhancing model robustness, and integrating multimodal and cross-modal data for more comprehensive anomaly detection frameworks. This paper underscores the necessity for continuous innovation in anomaly detection technologies to meet the evolving demands of industrial inspection, ultimately contributing to more reliable and efficient quality control systems.

1 Introduction

1.1 Significance of Anomaly Detection in Industrial Settings

Anomaly detection is essential for quality assurance and safety in industrial processes, focusing on both low-level structural and high-level semantic anomalies [1]. In Laser Additive Manufacturing (LAM), identifying defects such as porosity, cracks, and distortions is critical for preserving mechanical integrity and performance [2]. Similarly, in metal additive manufacturing, detecting rare events is vital for maintaining product quality and safety [3].

In Automated Fibre Placement (AFP) processes, anomaly detection ensures the quality of composite manufacturing by identifying defects that could compromise structural integrity [4]. Accurate detection of small, intricate defects on metallic surfaces is paramount for upholding high quality and safety standards [5].

Robust anomaly detection systems are crucial for bridging the gap between model training and real-world applications, particularly in environments where existing datasets may not fully reflect production complexities. These systems facilitate continuous training of deep learning models, adapting to new data and variations, thereby enhancing the efficiency, reliability, and safety of industrial processes. By employing effective data selection and filtering techniques, these systems mitigate risks associated with outdated models, ensuring optimal performance in real-time inspections and defect detection [6, 7, 8, 9, 10].

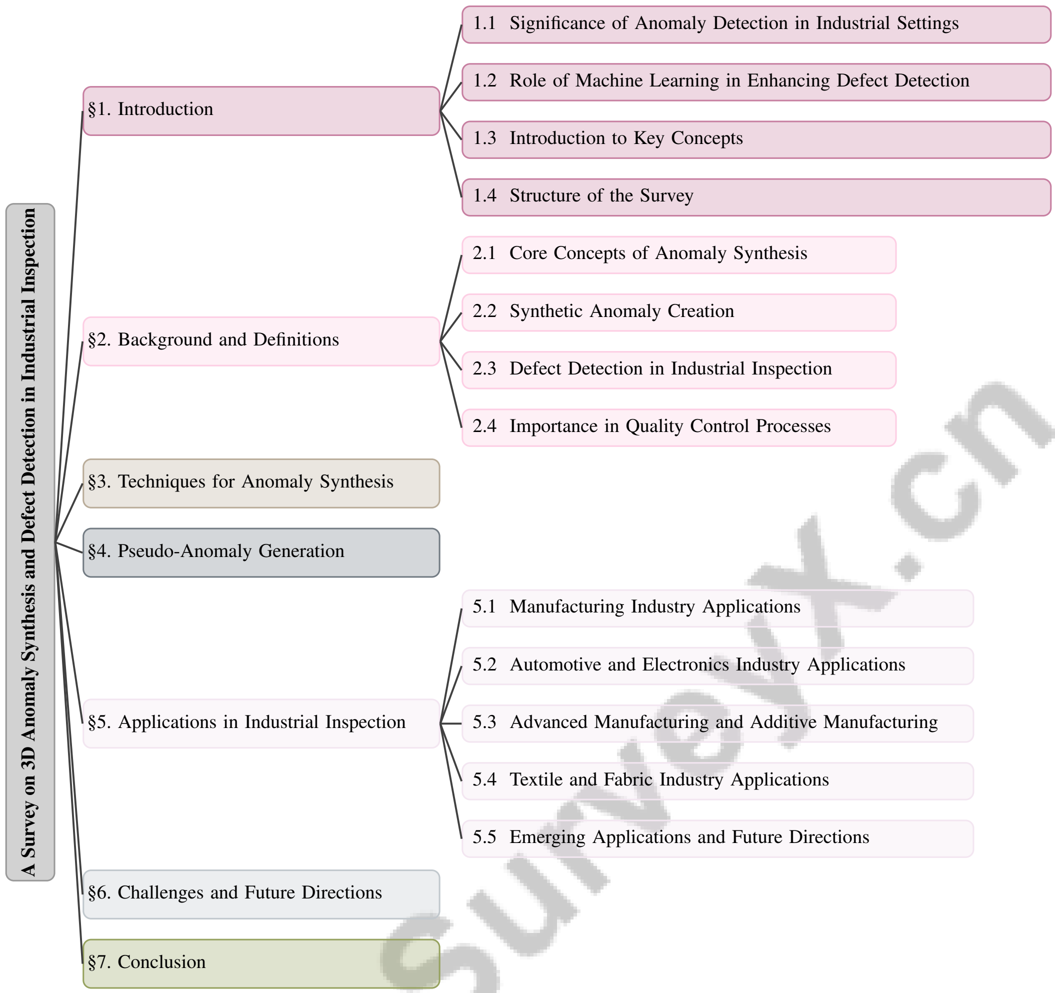

Figure 1: chapter structure

1.2 Role of Machine Learning in Enhancing Defect Detection

Machine learning has transformed defect detection in industrial settings, significantly improving accuracy and efficiency. Traditional methods often face challenges such as class imbalance and the need for extensive manual annotations, which machine learning addresses through advanced data-driven techniques [11]. The use of deep learning models on 3D point cloud data has notably enhanced detection precision in complex environments [12].

Recent advancements in unsupervised anomaly localization via deep learning have further improved defect detection effectiveness [13]. In semiconductor manufacturing, machine learning has successfully identified complex defect patterns, enhancing quality control processes [14]. In LAM, machine learning has also improved defect detection, addressing challenges posed by the stochastic nature of these processes [2].

The development of AI-Reasoner enhances the transparency and explainability of defect detection, making it more interpretable for industrial applications [15]. The Component-aware Anomaly Detection Framework (ComAD) further improves model adjustability and interpretability, enhancing performance in logical anomaly detection [1].

Innovative methods, such as combining unsupervised deep learning with classical computer vision techniques, enable defect detection and localization without labeled data, streamlining the process [4]. The application of graph neural networks (GNN) in additive manufacturing demonstrates machine learning's capability to model complex relationships with minimal labeled data [3].

Real-time defect detection has also seen enhancements through models like YOLOv5, which improve accuracy and efficiency, showcasing the ongoing evolution of machine learning in industrial applications [5]. The integration of machine learning not only addresses traditional method limitations but also fosters the development of adaptive, scalable, and robust solutions across various industrial contexts.

1.3 Introduction to Key Concepts

Anomaly synthesis and defect detection in industrial inspection are underpinned by several key concepts that drive advancements in quality control methodologies. A significant challenge in this domain is detecting rare anomalies, often exacerbated by underrepresented defects in training datasets [16]. Frameworks like DRÆM enhance anomaly detection by learning joint representations of anomalous images and their corresponding anomaly-free reconstructions [17].

Advanced data augmentation techniques are pivotal for improving anomaly detection capabilities. The CutPaste method, for instance, enhances one-class defect detection through innovative data augmentation strategies [18]. The InOut data augmentation strategy, which combines in-distribution samples generated by diffusion models with out-of-distribution samples, further strengthens defect detection capabilities [19].

Local feature analysis provides detailed geometrical insights about defects, offering more informative perspectives than global feature analysis [20]. Auto-encoders that reconstruct normal samples yield significant residuals for defects, facilitating effective anomaly detection without labeled defect images [11]. Technologies like laser ultrasonic visualization testing (LUVT) also demonstrate the potential for automating defect detection processes [21].

In image synthesis, controllable image synthesis (CIS) and pre-trained generative models support the creation of self-annotated defective images, establishing a robust framework for anomaly synthesis [22]. Automated feature extraction using deep learning, particularly with MFL data for pipeline inspections, exemplifies the integration of deep learning techniques in enhancing defect detection processes [23].

Transfer learning methods, such as TransferD2, facilitate defect identification across datasets of source objects, demonstrating adaptability in defect detection [24]. Automatic defect inspection algorithms utilizing Electron Microscopy (EM) image analysis categorize inspection algorithms into No Learning (NL), Machine Learning (ML), and Deep Learning (DL) [25].

The application of deep learning architectures, such as YOLOv3, in automated defect detection systems, particularly for PCBs, illustrates the role of advanced algorithms in industrial inspection [26]. Ongoing advancements in unsupervised anomaly localization and the evolution of methods from image-level to self-supervised learning techniques further highlight progress in this field [13].

Recent research emphasizes the complex and evolving landscape of anomaly synthesis and defect detection in industrial inspection, necessitating innovative and integrated methodologies. The Global and Local Anomaly co-Synthesis Strategy (GLASS) enhances anomaly detection by improving coverage and controllability for weak defects, while the Text-Align Anomaly Backbone Model (TAB) leverages visual-linguistic frameworks for improved performance in anomaly localization with minimal training data. The component-aware anomaly detection framework (ComAD) introduces adjustable and logical detection capabilities by segmenting images into components. Collectively, these approaches address the intricate challenges of industrial inspection, paving the way for more effective and adaptable solutions [27, 1, 28].

1.4 Structure of the Survey

This survey aims to explore the multifaceted domain of anomaly synthesis and defect detection within industrial inspection. It begins by emphasizing the importance of anomaly detection in industrial settings, which is crucial for maintaining quality and safety standards. The survey subsequently investigates the role of artificial intelligence (AI) and machine learning in enhancing defect detection capabilities, reflecting recent advancements [29].

Following the introduction, the paper provides a comprehensive background on essential concepts related to visual anomaly detection (VAD), including 3D anomaly synthesis, multimodal anomaly synthesis, pseudo-anomaly generation, and synthetic anomaly creation. The significance of these concepts in improving industrial inspection processes is highlighted, particularly in addressing challenges such as training data scarcity, diverse visual modalities, and complex hierarchical anomalies. The discussion includes innovative strategies like the Global and Local Anomaly co-Synthesis Strategy (GLASS), which enhances anomaly synthesis coverage and control, making it effective for detecting weak defects resembling normal regions [30, 28]. The techniques for anomaly synthesis are explored, focusing on methods like Generative Adversarial Networks (GANs), neural radiance fields, and advanced data augmentation techniques that contribute to realistic synthetic anomalies.

The survey also analyzes pseudo-anomaly generation, emphasizing its role in enhancing unsupervised anomaly detection by simulating rare defect scenarios. It discusses the incorporation of pseudo-anomalies into training processes to improve model sensitivity and discrimination capabilities while addressing challenges such as ensuring effective differentiation between normal and abnormal data [31, 32, 30, 33, 34]. Practical applications of synthetic anomaly creation and defect detection techniques across various industries are illustrated through case studies from sectors such as manufacturing, automotive, and electronics.

A thorough examination of current challenges in Visual Anomaly Detection (VAD) is presented, focusing on data scarcity, diverse visual modalities, and complex hierarchical anomalies, along with their implications for model generalization and computational costs. The survey outlines potential future research directions and technological advancements, emphasizing the need for innovative solutions to enhance VAD efficiency and effectiveness in applications like industrial defect inspection and medical image analysis [10, 30, 35]. The conclusion reinforces the significance of these advanced techniques in industrial inspection and suggests areas for future research and development.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Core Concepts of Anomaly Synthesis

Anomaly synthesis is pivotal in advancing defect detection models in industrial inspection, especially when anomalous data is scarce, a limitation of traditional methods that rely on normal instances alone [1]. In Laser Additive Manufacturing (LAM), techniques such as optical and acoustic monitoring, multisensor data fusion, and machine learning-assisted detection enhance capabilities in complex environments [2]. Unsupervised anomaly localization is crucial in identifying defects without labeled samples, addressing data scarcity and improving robustness [13]. This process is often challenged by weak defects near normal regions, which complicates detection.

Deep neural networks significantly contribute to anomaly synthesis, particularly in automatic defect detection and localization in Laser Ultrasonic Visualization Testing (LUVT) images. These networks analyze scattered waveforms to identify anomalies, meeting demands for efficient non-destructive testing as structural deterioration becomes more pressing. Generative models and deep convolutional networks have improved detection accuracy and computational efficiency, reducing reliance on human inspectors and ensuring reliable material integrity assessments [36, 21, 37]. Surface anomaly detection emphasizes the need for precise, localized detection capabilities.

Generative models address data scarcity in industrial anomaly detection by synthesizing defect images, enhancing unsupervised detection algorithms' ability to identify weak defects resembling normal patterns [38, 39, 31, 28]. This is supported by new datasets with comprehensive pose information and high-quality anomalies, advancing anomaly detection benchmarks. Accurate detection on textured surfaces is vital for product quality, necessitating sophisticated techniques. High-resolution imaging, like Electron Microscopy (EM), is crucial for precise image analysis in unsupervised detection, distinguishing abnormal from normal appearances. Advances in deep generative models enhance image quality and resolution in medical and industrial applications, improving anomaly detection algorithms [40, 25, 41].

Recent studies highlight the need for innovative anomaly synthesis strategies to tackle data scarcity and class imbalance. The Global and Local Anomaly co-Synthesis Strategy (GLASS) achieves state-of-the-art results in weak defect detection by enhancing coverage and controllability. The shift to unsupervised learning shows potential in overcoming supervised methods' limitations, which require extensive labeled datasets. Advancements in open-set supervised anomaly detection emphasize leveraging both seen and unseen anomalies to boost model robustness. These insights advocate for adaptive and efficient strategies in real-world industrial settings [38, 42, 43, 28].

2.2 Synthetic Anomaly Creation

Synthetic anomaly creation is essential for advancing defect detection models, addressing class imbalance, data scarcity, and the need for diverse training datasets in industrial inspection. By generating artificial anomalies, these techniques enhance datasets, improving model robustness and accuracy. The Global and Local Anomaly co-Synthesis Strategy (GLASS) exemplifies this by synthesizing anomalies at both feature and image levels, significantly enhancing weak defect detection [28].

Variational autoencoders (VAE) are instrumental in synthetic anomaly creation, with methods like VAE-based Synthetic Image Generation (VAE-SIG) augmenting datasets with synthetic images to overcome real defect sample scarcity [44]. Hierarchical generative models capture multi-scale patch distributions through transformations, improving representation and providing detailed contextual information for defect detection [45].

In multimodal anomaly creation, frameworks like CMDIAD use a Multi-modal Training, Few-modal Inference (MTFI) pipeline, enabling models to train on multiple inspection methods while allowing inference with one, leveraging diverse data inputs to improve detection capabilities [46]. Additionally, FMR-Net, an unsupervised framework, enhances visual inspection of textured surfaces by using both defect-free and synthetic defect samples, improving detection and restoration [47].

Advanced frameworks like 3DzAL employ contrastive learning and normalcy classification to learn patch-level relative normalcy, using pseudo abnormal 3D patch generation to enhance anomaly detection [48]. Techniques like Normal Background Regularization and Crop-and-Paste create augmented defect samples, improving segmentation model performance [49]. Data augmentation strategies, such as the CutPaste method, generate local irregularities in normal images, enhancing synthetic anomaly creation [18].

Synthetic anomaly creation is indispensable for advancing defect detection models, enabling effective learning from augmented datasets and improving generalization across diverse industrial contexts. The integration of synthetic data, as evidenced by the ADer benchmark, which combines real-world industrial and medical datasets with synthetic data, underscores the importance of comprehensive evaluation in enhancing model performance [50].

2.3 Defect Detection in Industrial Inspection

Defect detection is a cornerstone of quality control in industrial inspection, ensuring products meet specifications and maintain operational integrity. This involves identifying and classifying defects, from minor surface imperfections to significant structural anomalies, across various environments. In Laser Additive Manufacturing (LAM), defect detection is critical due to intricate thermal dynamics and process parameters influencing defect formation, affecting component quality and performance [2].

Effective classification and segmentation of defects in 3D point clouds are vital for condition monitoring and maintenance, improving detection accuracy and strategies while reducing downtime [12]. In Automated Fibre Placement (AFP), detecting surface defects is crucial for maintaining composite manufacturing quality, as these defects can compromise structural integrity and performance [4].

Metal additive manufacturing presents unique challenges due to high costs and difficulties in collecting labeled data. Detecting anomalies during manufacturing is essential for preventing defects that could lead to failures and increased costs [3]. Innovative methods like modified YOLOv5, with depthwise separable convolutions and channel shuffling, enhance small and complex defect detection on metallic surfaces, ensuring quality and safety [5].

Defect detection in industrial inspection requires continuous advancements in methodologies and technologies to address challenges like data scarcity, varying visual data backgrounds, and the demand for real-time detection. Leveraging state-of-the-art deep learning models and robust visual processing techniques enhances the digitization of previously inaccessible inspection data, improving machine health monitoring and ensuring industrial processes maintain efficiency and reliability while

AI-generated, for reference only.

consistently producing high-quality products. This supports the transition from manual to automated inspection systems [6, 8, 7, 10].

2.4 Importance in Quality Control Processes

Anomaly detection and synthesis are critical for maintaining high quality control standards across diverse industrial sectors, where product integrity and reliability are paramount. The unpredictability and rarity of anomalies necessitate sophisticated techniques for robust quality control. The complexity of defect patterns and variability introduced by manufacturing processes pose significant challenges, highlighting the need for extensive annotated datasets to train effective detection models [14]. However, reliance on large datasets is mitigated by innovative approaches like the Anomaly Detection Framework (ADF), which employs autoencoders trained solely on normal samples, eliminating the need for labeled defect data [4].

In the textile industry, intricate defect pattern detection is improved through dynamic and heuristic feature selection within CNN frameworks. This advancement addresses challenges posed by varying conditions and defect visibility, enabling manufacturers to enhance product quality and reduce waste. Recent research has developed a print fabric database and introduced a motif-based approach for unsupervised anomaly detection, streamlining the detection process by eliminating the need for extensive hyperparameter tuning and labeled data. This allows for real-time detection of a wide range of defects, including those from printing inconsistencies, addressing a critical gap in existing systems [51, 52]. This is crucial where defects significantly impact product quality and safety. Additionally, generating pseudo-anomalies is vital in scenarios of scarce defect samples, enhancing model robustness and transferability across datasets and contexts.

The development of comprehensive benchmarks facilitates systematic evaluation of unsupervised anomaly detection algorithms, providing a framework for comparing model performances across diverse defect types and imaging conditions. Despite advancements in industrial defect detection using machine learning and deep learning, existing benchmarks often lack comprehensive datasets representing the diverse range and severity of defects in specific applications, like Small Feature Regions (SFRs). This limitation hinders the effectiveness of detection algorithms, as many datasets lack precise labeling and real-world conditions necessary for robust model development and evaluation. A review of publicly available datasets highlights this issue, revealing that while some datasets like NEU-CLS and PCB Defect Dataset offer unique strengths, they do not fully encompass the variety of defects crucial for effective benchmarking and training in industrial contexts [53, 54].

Integrating advanced anomaly detection and synthesis techniques is crucial for ensuring high-quality control standards in industrial processes. These techniques address challenges such as data scarcity, annotation quality, and variability in manufacturing environments. For instance, the Global and Local Anomaly co-Synthesis Strategy (GLASS) significantly enhances unsupervised anomaly detection by synthesizing a broader range of anomalies, including subtle defects, while maintaining robust performance across datasets. Additionally, frameworks like the Discrepancy Aware Framework (DAF) demonstrate resilience against different synthetic data strategies, ensuring consistent detection accuracy. Moreover, innovative approaches in Automated Fibre Placement (AFP) combine unsupervised learning with classical methods to detect defects without extensive labeled data, optimizing the training process. These advancements highlight the importance of sophisticated anomaly detection frameworks in overcoming the limitations of traditional quality control methods [55, 28, 4, 27, 42]. These techniques empower industries to uphold product integrity and reliability, ensuring quality control processes remain efficient and effective in diverse manufacturing environments.

3 Techniques for Anomaly Synthesis

The synthesis of synthetic anomalies is crucial for enhancing the performance and reliability of detection models in anomaly detection. This section explores innovative anomaly synthesis techniques that advance industrial inspection methodologies. Table 2 presents a detailed comparison of innovative anomaly synthesis techniques, emphasizing their unique data generation methods, integration with machine learning frameworks, and application domains in the context of industrial inspection. The subsequent subsection focuses on Generative Adversarial Networks (GANs) and their variants, pivotal in generating realistic synthetic anomalies that significantly enhance defect detection model training.

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3.1 Generative Adversarial Networks (GANs) and Variants

GANs and their variants are essential for creating realistic synthetic anomalies that enhance defect detection model training. The GAN architecture, consisting of a generator and a discriminator, excels in producing high-fidelity synthetic data resembling real-world defects, addressing data scarcity and class imbalance issues prevalent in industrial settings [5]. By generating diverse datasets, GANs improve model robustness and accuracy, particularly where labeled defect data is scarce.

The adaptability of GANs is evident in their integration with other machine learning frameworks. Combining GANs with pre-trained generative models and data enhancement techniques allows for the generation of extensive datasets from limited source data, significantly improving defect detection accuracy [5]. Additionally, GANs' integration with deep learning algorithms, such as those in the YOLOv5 architecture, enhances automatic feature extraction, underscoring their broad applicability in refining anomaly detection methodologies on metallic surfaces [5].

As illustrated in Figure 2, the hierarchical structure of GANs and their variants plays a pivotal role in enhancing defect detection models. This figure emphasizes their function in generating synthetic anomalies, their integration with various machine learning frameworks, and their performance in real-world applications. GANs and their variants are instrumental in improving defect detection models by generating realistic synthetic anomalies, achieving high performance in classifiers with AUC scores of 0.9898 or higher, and addressing data imbalance issues in automated visual inspection processes. This effectiveness is demonstrated in research involving real-world data from Philips Consumer Lifestyle BV and advanced anomaly synthesis strategies like GLASS, which excels in detecting weak defects in industrial applications [56, 28]. Their ability to produce diverse, high-quality synthetic data and integrate with various machine learning techniques underscores their critical role in enhancing industrial inspection processes' accuracy and robustness.

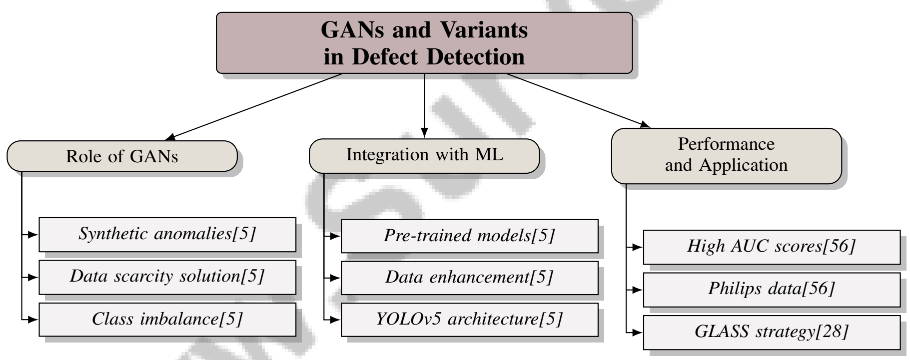


Figure 2: This figure illustrates the hierarchical structure of Generative Adversarial Networks (GANs) and their variants in enhancing defect detection models, emphasizing their role in generating synthetic anomalies, integration with machine learning frameworks, and performance in real-world applications.

3.2 Neural Radiance Fields (NeRF) and 3D Model Generation

NeRFs have revolutionized 3D model generation, particularly in anomaly synthesis for industrial inspection. By capturing images of standard and potentially defective models, NeRFs generate detailed 3D representations, facilitating comprehensive analysis of model differences and enhancing anomaly detection [57].

NeRFs utilize volumetric scene representation to reconstruct high-fidelity 3D models from 2D images, providing a robust framework for visualizing complex structures and identifying defects not apparent in traditional 2D inspections. Integrating NeRFs with sophisticated image processing techniques, such as CNNs and advanced pre-processing methods, allows for an intricate understanding of industrial components, improving defect detection accuracy and classification in challenging environments like additive manufacturing [7, 57, 49, 58, 59].

Applying NeRFs in anomaly synthesis has significant implications across various industrial sectors, facilitating precise 3D model generation crucial for effective quality control and assurance processes.

This is exemplified by frameworks like GLASS, which enhances anomaly synthesis coverage and controllability, enabling weak defect detection in complex environments [57, 60, 28, 27, 42]. The ability to create realistic 3D representations from limited visual data enhances anomaly detection and supports developing effective machine learning models for defect detection, underscoring NeRFs' importance in advancing industrial inspection systems.

Overall, deploying NeRFs in 3D model generation represents a significant advancement in anomaly synthesis techniques, providing a comprehensive approach to capturing and analyzing intricate industrial component details. This advancement facilitates creating robust and accurate defect detection models by integrating anomaly maps into supervised classification techniques, enhancing quality control processes across various industrial environments [27, 55].

3.3 Advanced Data Augmentation and Synthetic Data Techniques

Method Name	Techniques Employed	Application Domains	Challenges Addressed
HMKHA[61]	Image Editing	Industrial Quality Control	Data Scarcity
CP[18]	Cutpaste Method	Industrial Settings	Data Scarcity
MAE[62]	Image Reconstruction	Defect Detection	Data Scarcity
SSN[63]	Feature Maps	3D Printing	Imaging Conditions
Score-DD[64]	Iterative Denoising	Industrial Manufacturing	Data Scarcity
DSIT[65]	Binary Structured Light	Industrial Applications	Detection Accuracy
NDP-Net[66]	Reference-based Attention	Industrial Products	Class Imbalance
E2E-AI-AD[29]	3D Modeling Tools	Infrastructure Analysis	Data Scarcity

Table 1: Table summarizing various advanced data augmentation and synthetic data techniques employed in anomaly detection models. Each method is characterized by its specific techniques, application domains, and the challenges it addresses, highlighting their role in overcoming data scarcity and improving detection accuracy in industrial settings.

Advanced data augmentation and synthetic data techniques are crucial for enhancing anomaly detection models' performance and robustness. These methods effectively address class imbalance and data scarcity challenges, prevalent due to the infrequent occurrence of anomalies. By generating pseudo-anomalies and employing strategies like adversarially learned noise corruption, these techniques improve models' discriminative capabilities and accuracy across various datasets [33, 42, 39, 67].

A notable approach is the Human-machine knowledge hybrid augmentation method, employing image editing, style transfer, image filtering, and classification to generate and refine defect data, combining human expertise with machine learning to produce high-quality synthetic data [61]. The CutPaste method enhances anomaly detection by learning representations from normal data using augmentation and building a generative one-class classifier [18].

In self-supervised learning, using a Vision Transformer-based Masked Autoencoder (MAE) enhances anomaly detection models by leveraging robust feature learning from unlabeled data, improving generalization from limited labeled datasets [62]. The Semi-Siamese Network enhances defect detection accuracy by generating feature maps from reference schematics and camera images and calculating Euclidean distances [63].

Iterative denoising through stochastic differential equations (SDEs) synthesizes real images and detects defects, enhancing anomaly identification by iteratively refining data through noise reduction [64]. DSIT employs binary structured light for comprehensive illumination, detecting contaminants and defects without complex calculations, simplifying the detection process while maintaining high accuracy [65].

NDP-Net exemplifies integrating advanced techniques for enhancing anomaly detection capabilities, employing an encoder for feature extraction, a reference-based attention module for defect repair, and a multi-scale defect segmentation module for precise localization [66]. These approaches underscore the importance of leveraging advanced data augmentation and synthetic data techniques to develop effective and robust anomaly detection models, contributing to improved quality control processes in industrial settings.

Table 1 presents an overview of advanced data augmentation and synthetic data techniques, detailing the methods, their application domains, and the specific challenges they address in the context of enhancing anomaly detection models.

(a) Comparison of Drone and Ground-Based Images of a Power Line Structure[29]

(b) Simulated and Real X-ray Image Comparison[68]

Figure 3: Examples of Advanced Data Augmentation and Synthetic Data Techniques

As shown in Figure 3, the synthesis of anomalies and data augmentation plays a pivotal role in enhancing model robustness and accuracy. The example illustrates advanced techniques for data augmentation and synthetic data generation, showcasing practical applications through visual comparisons. The first part compares drone-captured and ground-based images of a power line structure, demonstrating how synthesized perspectives enhance dataset diversity and detail, crucial for training models to recognize and analyze infrastructure from various angles. The second part compares simulated and real X-ray images, highlighting synthetic data's importance in medical imaging. The simulated X-ray, despite lower resolution, is valuable for training models when real-world data is scarce. These examples underscore the significance of advanced data augmentation and synthetic data techniques in creating comprehensive datasets that bolster AI models' performance across diverse fields [29, 68].

3.4 Multimodal and Cross-Modal Anomaly Synthesis

Integrating multiple modalities in anomaly synthesis enhances detection accuracy in industrial inspection processes by leveraging the complementary strengths of various data modalities, such as audio, video, and 3D imaging. The combination of audio and video modalities significantly improves defect detection accuracy compared to traditional single-modality methods [69].

The CMDIAD framework exemplifies cross-modal anomaly synthesis by generating cross-modal hallucinations to compensate for missing modalities during inference, enhancing detection capabilities beyond traditional single-modality approaches [46]. Incorporating UAV technology with AI further illustrates multimodal anomaly synthesis benefits, providing diverse data inputs that enhance detection models' robustness and precision [70]. The modular structure of DefectOnt aligns with existing ontologies, allowing comprehensive defect representation and enhancing anomaly synthesis and detection processes [71].

The continual learning framework with out-of-distribution detection represents an innovative approach to improving anomaly detection in manufacturing settings, allowing models to adapt to new data while maintaining detection accuracy, highlighting dynamic learning strategies' importance in multimodal anomaly synthesis [72]. Furthermore, the GLASS framework synthesizes a broader range of anomalies, enhancing detection capabilities for weak defects compared to existing methods [28]. The self-supervised iterative refinement process (IRP) contributes by adaptively refining training data, minimizing outliers' influence, and enhancing model robustness against noise [73].

Integrating multiple modalities in anomaly synthesis significantly improves defect detection technologies, enabling accurate and robust quality control processes across diverse industrial applications. This approach enhances complex and subtle anomaly detection by incorporating pseudo-anomaly generation techniques, improving models' ability to differentiate between normal and abnormal data. Additionally, it facilitates developing adaptive and scalable detection models applicable across various domains and data types, such as images, videos, and time series, addressing traditional one-class classification methods' limitations in anomaly detection [39, 74, 43, 33, 75].

4 Pseudo-Anomaly Generation

4.1 Concept and Importance of Pseudo-Anomaly Generation

Pseudo-anomaly generation is pivotal in anomaly detection, particularly in industrial inspection where true anomalies are infrequent. This technique synthesizes anomalies from normal data, simulating

Feature	Generative Adversarial Networks (GANs) and Variants	Neural Radiance Fields (NeRF) and 3D Model Generation	Advanced Data Augmentation and Synthetic Data Techniques
Data Generation Method	Realistic Synthetic Data	3D Model Generation	Pseudo-anomalies Generation
Integration with Frameworks	Deep Learning Algorithms	Image Processing Techniques	Self-supervised Learning
Application Domain	Industrial Inspection	Additive Manufacturing	Various Datasets

Table 2: This table provides a comprehensive comparison of three cutting-edge techniques in anomaly synthesis: Generative Adversarial Networks (GANs) and their variants, Neural Radiance Fields (NeRF) for 3D model generation, and advanced data augmentation and synthetic data methods. It highlights the key features of each approach, including data generation methods, integration with existing frameworks, and their respective application domains, illustrating their distinct contributions to enhancing industrial inspection processes.

out-of-distribution events to enhance model robustness and generalization. It reduces dependence on extensive labeled datasets by generating variations of normal appearances, allowing models to learn from a broader data spectrum [76]. The method significantly boosts models' discrimination capabilities, such as autoencoders, improving anomaly detection performance by simulating rare defect scenarios [3]. Techniques like DRÆM leverage synthetic anomalies from anomaly-free images to bolster model robustness and enable effective anomaly localization without actual anomaly samples [76].

In industrial contexts, pseudo-anomaly generation is crucial for real-time monitoring and quality assurance, predicting defect severity, and simulating rare scenarios to maintain high-quality standards. The incorporation of graph neural networks (GNN) underscores its relevance, enhancing anomaly detection without extensive labeled datasets [3]. This approach addresses data imbalance and anomaly scarcity, advancing defect detection technologies. Techniques like the Iterative Refinement Process (IRP) and DRÆM, using cyclic data refinement and anomaly mapping, respectively, significantly improve detection accuracy in noisy, sparse environments. Models like the TAB framework, integrating visual and text-aligned embeddings, further optimize anomaly detection, enhancing reliability and efficiency across diverse industrial applications [27, 73, 55].

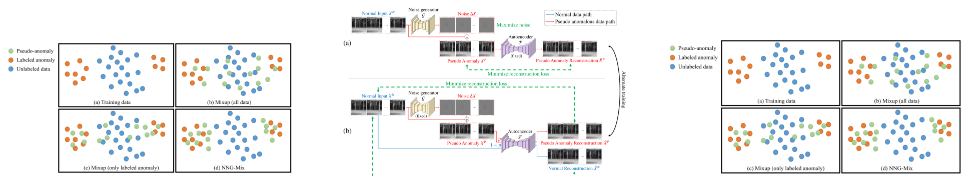
4.2 Pseudo-Anomaly Generation Techniques

Techniques for pseudo-anomaly generation are essential for simulating rare defect scenarios, enhancing anomaly detection models' robustness and performance. The NNG-Mix technique, which combines labeled anomalies with their top k nearest neighbors from unlabeled data and adds Gaussian noise, effectively simulates rare defects by introducing controlled variations, improving generalization from limited datasets [77]. Random masking of normal data fosters learning of normalcy representations by creating pseudo-anomalies, challenging models to differentiate normal from anomalous patterns [32].

The STPAG technique exemplifies pseudo-anomaly generation by inpainting normal video frames and perturbing optical flow, enhancing anomaly detection in video data by simulating rare defect scenarios in a spatio-temporal context [78]. Similarly, GANs generate pseudo-anomalies that are distinct yet reflective of normal data distributions, enabling rare defect scenario simulation without extensive labeled datasets [33]. Techniques involving inpainting and optical flow perturbation enhance subtle anomaly detection by simulating realistic defect scenarios [79].

These techniques are crucial for enhancing defect detection models, offering realistic training scenarios that address the scarcity of actual anomalous data. By incorporating pseudo-anomalies into training, models improve sensitivity to normal-abnormal differences, enhancing anomaly classification performance. This advancement is significant for developing robust detection systems applicable in diverse settings, such as video surveillance, where identifying unexpected behaviors is critical for safety and efficiency [33, 34].

As depicted in Figure 4, pseudo-anomaly generation techniques enhance detection models' robustness and accuracy. The examples highlight methodologies leveraging pseudo-anomalies to improve detection capabilities. "Anomaly Detection with Mixup and NNG-Mix" combines labeled and unlabeled data to refine the detection process, while "Anomaly Detection via Noise-Driven Autoencoder" uses noise-driven autoencoders alternating between normal and pseudo-anomalous data, effectively training models to distinguish between normal and anomalous patterns. These techniques underscore the significance of pseudo-anomaly generation in advancing detection systems, illustrating how synthetic anomalies can train more accurate and resilient models [77, 39, 80].



(a) Anomaly Detection with Mixup and NNG-Mix[77]
(b) Anomaly Detection via Noise-Driven Autoencoder[39]
(c) Anomaly Detection with Mixup and NNG-Mix[80]

Figure 4: Examples of Pseudo-Anomaly Generation Techniques

4.3 Challenges in Pseudo-Anomaly Generation

Generating effective pseudo-anomalies poses challenges impacting anomaly detection models' performance. A primary challenge is creating pseudo-anomalies that accurately represent real-world defects' diversity and complexity, which can limit models' generalization to unseen anomalies [77]. Overfitting is another concern, where models trained on synthetic pseudo-anomalies excel on artificial data but struggle with genuine anomalies, due to a lack of variability and realism in the generated data [33].

Balancing pseudo-anomaly generation while maintaining normal data distribution integrity is challenging. Techniques perturbing normal data must ensure pseudo-anomalies are distinct from and representative of normal patterns. Failure to achieve this balance can lead to models that are overly or insufficiently sensitive to anomalies, affecting reliability [78]. The computational cost of generating high-quality pseudo-anomalies is another hurdle. Techniques involving GANs or complex processes require substantial resources, which can be prohibitive in large-scale applications. The need for real-time processing capabilities in industrial settings, where timely detection is critical, compounds this challenge [77].

Addressing these challenges is crucial for enhancing anomaly detection models' effectiveness. By improving pseudo-anomalies' realism and diversity while balancing computational efficiency with detection accuracy, more robust models can navigate industrial complexities. These models demonstrate improved discriminative capabilities in various datasets, such as CUHK Avenue and ShanghaiTech, showing significant ability to differentiate normal from anomalous frames. This advancement is vital given the rarity of true anomalies, necessitating innovative approaches like synthetic pseudo-anomalies and advanced training techniques [31, 39, 32, 55, 33].

5 Applications in Industrial Inspection

Advanced technologies are pivotal in industrial inspection, significantly enhancing product quality and operational efficiency. This section delves into the specific applications of anomaly detection and synthesis techniques across various industries, with a focus on their transformative impact on quality control processes. The manufacturing sector, in particular, benefits from these techniques by substantially improving defect detection capabilities and maintaining rigorous quality standards.

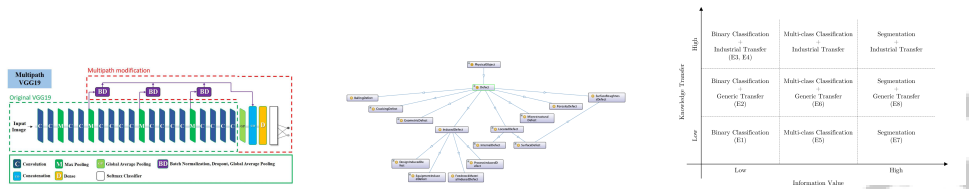
5.1 Manufacturing Industry Applications

In the manufacturing industry, anomaly detection and synthesis techniques have markedly improved quality control by enhancing defect detection and localization. For example, the Automated Fibre Placement (AFP) composites framework achieves over 98

Synthetic anomaly generation techniques augment quality control by creating diverse datasets for training robust defect detection models. This approach tackles the challenge of limited labeled defect data in industrial settings by leveraging abundant defect-free samples and employing methods like Normal Background Regularization and data augmentation through crop-and-paste operations to enhance defect segmentation networks [49, 27].

Deep learning models in visual quality inspection have improved processing speeds and reduced network traffic, facilitating real-time defect detection. This capability optimizes production lines and minimizes downtime due to quality defects, ultimately enhancing manufacturing efficiency through automated image processing and machine learning [81, 7, 10, 82].

Advancements in machine learning, particularly in image processing and defect detection, highlight the pivotal role of innovative technologies in enhancing manufacturing processes. Techniques such as Deep Convolutional Neural Networks (CNNs) enable real-time defect identification during additive manufacturing, while fog computing enhances data processing capabilities in industrial inspections [10, 58, 83, 7].



(a) Multipath VGG19: A Novel Architecture for Image Classification[84]

(b) Defects in Physical Objects[71]

(c) Knowledge Transfer and Information Value in Machine Learning Models[85]

Figure 5: Examples of Manufacturing Industry Applications

As depicted in Figure 5, the application of advanced machine learning and image processing techniques in manufacturing exemplifies significant improvements in defect detection. The "Multipath VGG19" architecture enhances image classification by identifying intricate patterns in industrial images. The hierarchical classification of "Defects in Physical Objects" provides a framework for categorizing defect types essential for quality control. Furthermore, the interplay between knowledge transfer and machine learning models highlights optimization strategies for improved performance in industrial applications [84, 71, 85].

5.2 Automotive and Electronics Industry Applications

In the automotive and electronics sectors, anomaly detection and synthesis techniques have significantly enhanced product quality and operational efficiency. In automotive manufacturing, advanced frameworks are vital for identifying potential defects in critical components, such as airbags. Through image processing and machine learning, manufacturers detect defects like missed stitches in airbag seams early in production, aligning with the industry's focus on real-time monitoring to mitigate safety risks [86, 35, 9, 10, 27]. Generative Adversarial Networks (GANs) are also utilized to create synthetic anomalies that enhance the training of robust defect detection models, improving the identification of rare defects.

In electronics, where precision is paramount, advanced anomaly detection techniques, including machine learning and deep learning, streamline inspection processes for electronic components. Frameworks like YOLOv3 and Faster R-CNN enable automated defect detection, enhancing accuracy and efficiency while reducing reliance on manual inspection [1, 55, 38, 25, 26]. Deep learning models for defect detection in printed circuit boards (PCBs) exemplify the successful application of these techniques, facilitating automatic identification of defects and increasing detection accuracy.

Successful case studies in electronics demonstrate the effectiveness of synthetic data augmentation techniques in improving defect detection model performance. By generating diverse synthetic datasets, these methods address data scarcity in manufacturing environments, reducing costs associated with data collection and enhancing models' generalization capabilities across various defect types [87, 68].

The application of anomaly detection and synthesis techniques in the automotive and electronics industries underscores their critical role in advancing quality control processes. By employing improved neural networks and anomaly map-assisted classification, manufacturers can effectively tackle challenges posed by small datasets and complex visual inspections, leading to enhanced product quality and consumer trust [55, 88, 89].

5.3 Advanced Manufacturing and Additive Manufacturing

Anomaly synthesis plays a crucial role in enhancing manufacturing processes, particularly in additive manufacturing (AM), by facilitating unsupervised anomaly detection of subtle defects. Recent advancements, such as the Global and Local Anomaly co-Synthesis Strategy (GLASS), have achieved state-of-the-art results in defect detection by synthesizing a broader range of anomalies. In-situ anomaly detection methods utilizing machine learning models, including graph neural networks, show promise in predicting rare defect-inducing events during metal additive manufacturing, thereby reducing inspection costs [3, 28].

In additive manufacturing, synthetic anomalies are crucial for addressing defects like porosity and misalignment, which compromise product performance. By generating synthetic anomalies that mimic rare defects, manufacturers can train machine learning models to recognize these issues, significantly enhancing reliability and quality. This approach mitigates challenges associated with limited annotated defect data and improves model performance by integrating simulated data with real images [87, 39].

The incorporation of synthetic data in training models effectively addresses the challenge of limited labeled defect data in the AM industry, reducing costs associated with data acquisition and enhancing model performance through diverse training samples. By leveraging both synthetic and real-world data, researchers have demonstrated improved detection capabilities while minimizing reliance on extensive manual labeling efforts, ultimately streamlining quality inspection processes [87, 56, 68, 29].

Anomaly synthesis significantly enhances quality control mechanisms in advanced and additive manufacturing. Techniques like GLASS improve the detection of subtle defects, achieving high accuracy in industrial applications such as woven fabric defect detection. In-situ anomaly detection methods employing graph neural networks have successfully monitored metal additive manufacturing processes, achieving notable defect detection performance. Furthermore, innovative techniques in 3D printing, including Region of Interest selection and CNNs, have achieved perfect accuracy in defect localization, underscoring the importance of advanced anomaly detection methods in modern manufacturing environments [4, 58, 3, 28].

5.4 Textile and Fabric Industry Applications

Anomaly detection and synthesis techniques have notably improved defect detection systems in the textile and fabric industries, ensuring high quality and efficiency. The complexity of textile patterns and textures complicates the detection of defects such as weaving errors and color mismatches. The integration of advanced machine learning algorithms with synthetic data generation techniques has effectively enhanced defect detection accuracy and reliability. By combining real-world drone imagery with photorealistic synthetic images, models can identify rare defects without extensive manual labeling, achieving performance improvements of 67

The application of genetic algorithms in the textile industry highlights the potential for real-time defect identification, optimizing detection processes to adapt to specific textile characteristics [90]. Moreover, synthetic anomaly creation techniques generate diverse training datasets essential for robust detection models, enhancing the ability to generalize across various fabric types and production conditions. This leads to more efficient quality control processes, enabling rapid anomaly detection and minimizing production downtime [91, 92, 93, 52].

The implementation of advanced anomaly detection and synthesis techniques in the textile industry is crucial for enhancing defect detection capabilities. Approaches like GLASS improve the identification of weak defects, while automated inspection systems leveraging computer vision address challenges in defect detection and classification. These methodologies streamline quality control processes, reduce fabric wastage, and lower production costs, reinforcing their importance in maintaining competitiveness in the global market [52, 94, 92, 28, 91].

5.5 Emerging Applications and Future Directions

Emerging applications of anomaly detection and synthesis techniques are gaining recognition across various industrial settings, enhancing operational efficiency and product quality. In smart manufactur-

AI-generated, for reference only.

ing, the integration of IoT devices with advanced anomaly detection algorithms facilitates real-time monitoring and predictive maintenance, improving reliability and reducing downtime [72].

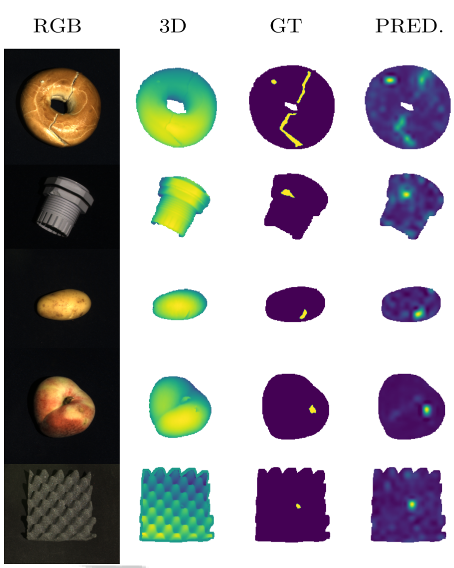
The energy sector is adopting these techniques to monitor critical infrastructure, such as power grids and wind turbines, by analyzing sensor data for anomalies to predict equipment failures and optimize maintenance schedules [71].

In autonomous vehicles, anomaly detection and synthesis are vital for ensuring the safety and reliability of self-driving systems. These techniques identify unexpected events—like sensor malfunctions—using methods such as video anomaly detection and open-set supervised anomaly detection, enhancing decision-making capabilities by recognizing both familiar and novel anomalies [34, 43].

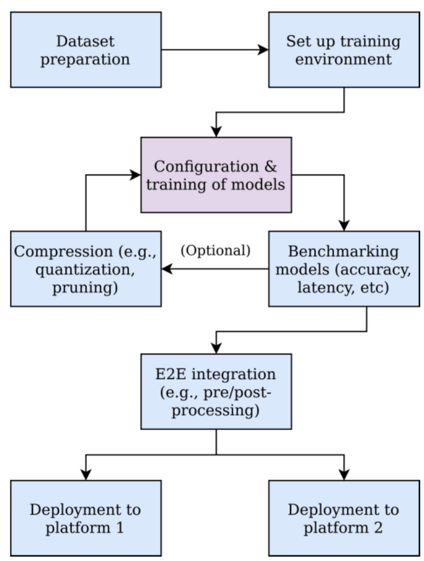
Future developments in sophisticated anomaly detection models leveraging advancements in AI and machine learning are anticipated. These models will handle complex data inputs, including multimodal and cross-modal data, providing comprehensive insights into industrial processes [69].

The integration of quantum computing with anomaly detection algorithms could revolutionize the field by increasing computational efficiency and enabling the analysis of larger datasets. This advancement may lead to next-generation quality control systems that enhance inspection processes through faster and more accurate defect detection, adaptable to modern industrial requirements [95, 81, 10].

The ongoing advancement of techniques such as GLASS and component-aware frameworks is expected to enhance industrial inspection processes, improving the accuracy of subtle defect detection while reducing reliance on extensive labeled datasets. These developments will contribute to more efficient, reliable, and sustainable industrial systems, transforming quality control in manufacturing [38, 1, 28].



(a) Comparison of RGB, 3D, Ground Truth (GT), and Predicted (PRED.) Segmentation Results for Various Objects[96]



(b) Flowchart of a Machine Learning Model Deployment Process[97]

Figure 6: Examples of Emerging Applications and Future Directions

As depicted in Figure 6, the integration of advanced technologies such as machine learning and 3D imaging is fostering innovative applications in industrial inspection. One notable example is the comparison of segmentation results using RGB, 3D, Ground Truth (GT), and Predicted (PRED.) images, showcasing improvements in precision and accuracy for object classification. Additionally, a detailed flowchart illustrates the machine learning model deployment process, encompassing steps from dataset preparation to model deployment, including training environment setup, model configuration, and performance benchmarking. These examples highlight the transformative potential of machine learning and 3D imaging in enhancing industrial inspection processes, pointing towards a future of heightened efficiency and accuracy [96, 97].

AI-generated, for reference only.

6 Challenges and Future Directions

Addressing the multifaceted challenges in anomaly detection and synthesis requires a comprehensive exploration of the factors affecting these systems' effectiveness. Key issues include data scarcity and quality, model generalization and robustness, computational efficiency and scalability, and the integration of advanced technologies. As illustrated in Figure 7, the hierarchical categorization of these challenges and future directions emphasizes these critical areas, while also identifying additional research opportunities that may enhance the efficacy of anomaly detection systems. This visual representation not only consolidates the discussion but also serves as a roadmap for future inquiries in the field.

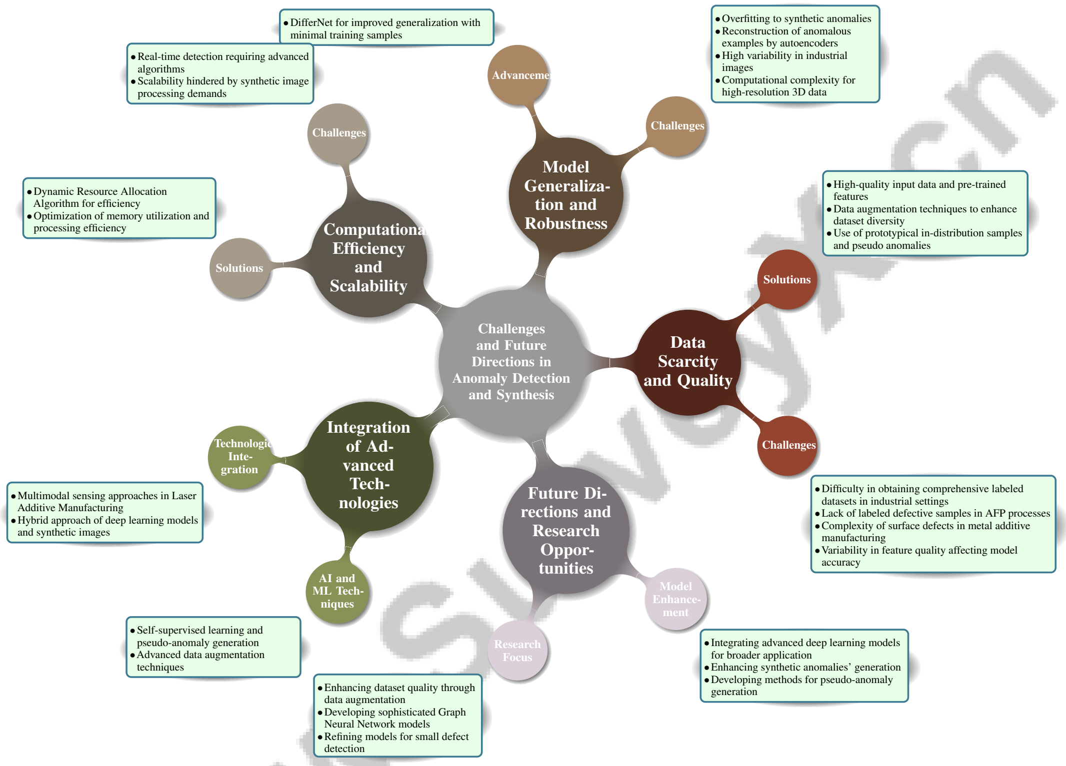


Figure 7: This figure illustrates the hierarchical categorization of challenges and future directions in anomaly detection and synthesis, highlighting key areas such as data scarcity and quality, model generalization and robustness, computational efficiency and scalability, integration of advanced technologies, and future research opportunities.

6.1 Data Scarcity and Quality

Data scarcity and quality present significant hurdles in developing anomaly detection models, particularly in industrial settings where obtaining comprehensive labeled datasets is challenging. The lack of labeled defective samples is especially problematic in Automated Fibre Placement (AFP) processes, complicating effective defect detection systems [4]. This is further compounded in metal additive manufacturing, where the complexity of surface defects under real-world conditions highlights existing methods' inadequacy.

Current models often rely on extensive labeled datasets, but the quality of features like DefChars can vary significantly depending on image conditions and defect types [15]. This variability necessitates high-quality input data critical for model accuracy [14]. Additionally, pre-trained features may not capture all necessary details for complex scenarios, limiting model effectiveness [1].

The challenge of data scarcity is pronounced in dynamic industrial environments, where models must be optimized for larger datasets and faster processing cycles to maintain efficiency. Innovative data augmentation techniques are essential to enhance dataset diversity and model robustness [5]. Recent strategies, such as using prototypical in-distribution samples and generating pseudo anomalies, show promise in improving model performance with minimal training data, enhancing the differentiation between normal and abnormal data [31, 39, 43, 30, 75].

6.2 Model Generalization and Robustness

Model generalization and robustness are critical challenges, especially in industrial applications where models must adapt to various defect types and conditions. Overfitting to synthetic anomalies often leads to poor generalization to real-world anomalies [42]. Autoencoders trained solely on normal data may reconstruct anomalous examples, reducing anomaly detection effectiveness [98].

High variability in industrial images complicates defect detection and segmentation [99]. Models must adapt to diverse defect patterns, a limitation of current methods. The dependency on training data quality also poses challenges, as models may struggle with defect types not in the training set [100].

Computational complexity and memory requirements for high-resolution 3D data and unstructured point clouds further challenge model robustness [12]. Despite these challenges, advancements like DifferNet demonstrate potential for improved generalization, outperforming existing methods with minimal training samples [101].

6.3 Computational Efficiency and Scalability

Anomaly detection in industrial settings faces challenges related to computational efficiency and scalability. Processing high-resolution data for real-time detection requires advanced algorithms that handle large volumes without compromising performance. The Dynamic Resource Allocation Algorithm (DRAA) reallocates resources based on performance metrics, enhancing efficiency in large-scale applications [37].

Scalability is often hindered by computational demands of generating and processing synthetic images. While synthetic data augments training datasets, it may not capture all real defect characteristics, affecting detection accuracy [102]. Continuous refinement of synthetic data generation methods is necessary to ensure accurate representation of real-world anomalies.

Integrating anomaly detection models into industrial processes requires efficient algorithms that scale with increasing data volumes and complexity. Optimizing memory utilization and processing efficiency is crucial for scalability and effectiveness, particularly in fields like industrial anomaly detection, where advanced frameworks and multimodal large language models (MLLMs) enhance performance with minimal data requirements [103, 104].

6.4 Integration of Advanced Technologies

Integrating advanced technologies into anomaly detection processes holds potential for overcoming challenges and enhancing system capabilities. Multimodal sensing approaches provide comprehensive understanding by combining data from various sources, particularly in Laser Additive Manufacturing (LAM), where fusing optical, acoustic, and thermal data improves defect detection models' accuracy [2].

Enhancing machine learning models for real-time applications is crucial, particularly in asset inspection and defect detection, where combining synthetic data with real-world imagery improves accuracy and reduces manual labeling efforts. A hybrid approach of deep learning models and synthetic images can achieve up to 92

Integrating AI and ML techniques, including deep learning and reinforcement learning, improves models' adaptability and robustness through self-supervised learning (SSL) and pseudo-anomaly generation. These strategies enhance model performance by utilizing unlabeled data and improving discriminative capability through synthetic anomaly generation [39, 43, 33, 42, 75]. Advanced data augmentation techniques generate synthetic datasets to address data scarcity and enhance model robustness, improving anomaly detection coverage and controllability [27, 29, 28].

6.5 Future Directions and Research Opportunities

Future research in anomaly detection and synthesis will explore innovative pathways to enhance model robustness and applicability. Enhancing dataset quality through advanced data augmentation can improve defect detection models' precision by generating comprehensive training datasets [4]. Developing sophisticated Graph Neural Network (GNN) models represents a critical direction, enhancing performance and generalization capabilities [3].

Future research will also focus on refining models to detect small defects and adapting them for a wider range of scenarios [5]. Integrating advanced deep learning models could extend defect detection systems' application to more defect types, improving sensitivity to subtle anomalies with minimal training samples [31, 33].

Enhancing synthetic anomalies' generation and refining models for broader real-world anomaly generalization is crucial. Developing methods for pseudo-anomaly generation can improve models' performance trained primarily on normal data. Techniques like GLASS and other frameworks have shown promise in increasing models' sensitivity to subtle defects [39, 32, 28, 33, 34].

Enhancing model robustness through self-supervised learning and developing methods that generalize across different industrial images are critical for future exploration. Engaging in these research opportunities will advance anomaly detection and synthesis, developing more robust and adaptable models capable of addressing industrial applications' evolving demands [38, 43, 28].

7 Conclusion

This survey underscores the transformative advancements in anomaly synthesis and defect detection, highlighting their crucial impact on industrial inspection processes. The integration of synthetic datasets with real-world data has significantly improved defect detection accuracy, particularly in asset and defect identification. Techniques employing Variational Autoencoders (VAEs) demonstrate the potential of synthetic data in developing Intelligent Cognitive Systems (ICS) with high classification accuracy, showcasing the value of synthetic datasets in model training.

The survey also identifies key challenges in Visual Anomaly Detection (VAD), emphasizing the need for comprehensive, multimodal frameworks to enhance detection capabilities across diverse industrial applications. Advanced methods like Detectron2 have shown effectiveness in defect identification and segmentation, bolstering quality control in manufacturing. The Global and Local Anomaly co-Synthesis Strategy (GLASS) has set new benchmarks in anomaly detection, particularly in synthesizing and detecting subtle defects across various datasets.

Moreover, the robustness of methods such as the RFS Energy approach and FMR-Net in detecting defects on textured surfaces illustrates the efficacy of these techniques in industrial contexts. The importance of standardizing monitoring techniques and harnessing machine learning to enhance defect detection capabilities are identified as pivotal areas for future research and development.

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