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RESEARCH PAPER

Applications of Deep Learning Approaches for Defect Identification: Trends, Challenges, and Future Directions

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***Abstract*—Quality assurance in many fields relies on the ability to detect defects. This is especially true in the manufacturing, construction, electronics, and medical diagnostics sectors. As deep learning becomes more prevalent in industrial inspection systems, its revolutionary effect on defect identification is being felt in many different fields. This article summaries current methods for detecting defects in manufacturing, infrastructure, and biomedical imaging using deep learning. It examines methods such as CNNs, generative models, attention mechanisms, and emerging transformer and diffusion frameworks, focusing on their effectiveness in surface anomaly detection. The paper categorizes approaches into supervised, unsupervised, and semi-supervised models, examining their suitability under different data conditions and deployment scenarios. It also highlights key implementation challenges, including data imbalance, annotation complexity, dataset variability, and generalization across domains. There are also important items like the quality of the dataset, model interpretability, scalability, and real-time performance that are mentioned to ensure the successful implementation of AI in real-world scenarios. Future directions include the emergent technologies of domain-adaptive learning, explainable AI and the deployment of AI at the edge, where it could be applied to real-time inspection. The review summarizes the recent advances and highlights the methodologies to enhance the transparency and reliability of deep learning-based defect detection and the emergence of intelligent and high-performance adaptive inspection devices in industries.**

Keywords—Deep Learning, Defect Detection, Convolutional Neural Networks (CNN), Generative Models, Quality Inspection, Smart Manufacturing.

I. Introduction

In industrial quality control, the detection of defects is an important process. Manual inspections with special tools are traditionally achieved by experts in order to detect defects [1]. But the drawback of this method is that it is time-consuming, labor-intensive, and it is also prone to fatigue-related errors, particularly in settings that need constant vigilance [2]. Consequently, the trend has been to move to Infrastructure Automated Defect Detection (IADD), which involves the application of deep learning models to increase speed, consistency and reliability in defect detection.

Deep learning (DL), a subfield of machine learning (ML), has become a prominent tool for automating the process of defect detection in particular industrial fields over the past several years [3]. As opposed to traditional computer vision techniques, which are based on handcrafted features, DL models, and, in particular, Convolutional Neural Networks (CNNs) have the ability to learn discriminative features without relying on handcrafted features and explore the raw data automatically [4]. This gives them a high degree of effectiveness in the detection of delicate and complex flaws in structural systems and manufactured parts. In addition to CNNs [5]. The recent innovations, including generative models, attention-based models, hybrid frameworks, and diffusion-based models, have boosted the potential of DL and given it a more reliable opportunity to perform well under complex [6] real-life conditions, which are highly diverse.

In high-tech manufacturing, assembly and test of semiconductors (SAT), Automated Optical Inspection (AOI) is the norm in yield management. The huge amount of defect images generated by the AOI systems is usually processed offline by human operators, and is time-consuming and prone to error due to visual fatigue. To meet this, Automated Defect Classification (ADC) tools are implemented in Industry 4.0 to cut down on manual efforts and operational expenses in high-volume manufacturing (HVM).

Despite these advancements, one of the primary challenges in deploying DL models for defect detection is the requirement for large and diverse datasets. In practice, it may be quite challenging to collect a number of images of defective products, especially in the case of rare defective products or types of defects that are emerging [7][8]. This constraint poses a major impediment to training complex DL architectures, e.g., Vision Transformers (ViTs), that require large data volumes in order to work effectively.

In conclusion, even though DL has the potential to transform the whole field of automated defect detection in industries, many obstacles still exist, particularly in terms of data availability, generalization, and real-time deployment. Current research is still trying to tackle these problems by optimizing the models, extending the available data, and transferring the results of one domain to another.

A. Structure of the Paper

The structure of this paper is as follows: Section II presents key DL techniques used for defect detection. Section III discusses major application domains and industrial use cases. Section IV outlines data-related challenges and future research opportunities. Sections V and VI present the summary of the literature and conclude with insights and potential advancements in the field.

II. Deep Learning Techniques for Defect Detection

DL has digitalized defect detection because it allows automatic feature extraction, robust pattern recognition, and eases the deployment process into various industrial fields. This section reviews important DL structures, CNNs, AEs, and GANs that have proved to be very successful in detecting and localizing surface anomalies. All the models have different contributions. CNNs give the possibility of high-throughput classification, AEs allow the localization of defects in an unsupervised manner, and GANs allow data diversity and anomaly detection to be enhanced [9]. These basic concepts, architectural differences, uses, and constraints provide a comprehensive understanding of how they can be used to enhance defect detection capabilities and shape future research in the sphere of model optimization and hybrid implementation.

A. Convolutional Neural Networks (CNNs)-Based Models

CNNs are DL models that handle data with a grid layout, such as pictures. Their architecture mimics that of the animal visual cortex, allowing them to effortlessly and adaptively learn feature hierarchies ranging from simple to complex patterns. Because users must manually create defect features using traditional surface defect detection methods, their capacity to handle complex features may be limited [10]. The characteristics that influence defect identification, however, may be automatically identified using CNNs.

Key characteristics of CNN-based models in defect detection:

- **Feature Extraction:** The process of identifying and extracting key physical and visual attributes from images of produce. These features, such as colour, texture, shape, and size, serve as inputs for ML classifiers, enabling accurate categorization of produce based on its quality.
- **Translation invariance:** The ability to detect defects regardless of their position within the image, ensuring consistent and reliable performance in dynamic inspection environments.
- **Real-time application:** Leveraging advanced GPUs and specialized DL frameworks, CNNs are capable of processing images at near real-time speeds, facilitating high-throughput and efficient industrial inspection [11].

Common CNN Architectures Used in Defect Detection:

- **Alex Net and VGG Net:** The most well-known engineering tool used to manage DL is VGG Net. In any case, it is similar to Alex Net's 3 x 3 convolutions with more channels.
- **ResNet:** Listens to the issue of the vanishing gradient and allows deeper networks, which enhances defect localization and segmentation.
- **Mobile Net and Efficient Net:** Low-weight models applicable to an edge deployment for mobile on-device inspection.

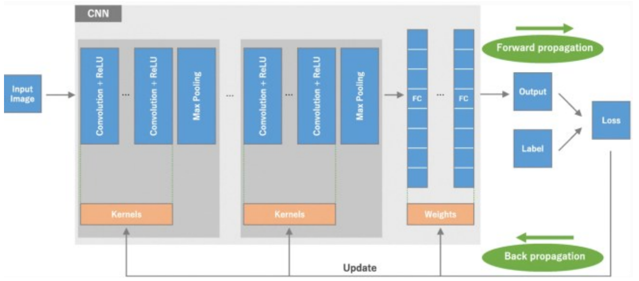

Fig. 1. Convolutional neural network (CNN) architecture and the training process

A challenge related to CNNs is that they are sensitive to variations in illumination and easily suffer from overfitting with small datasets, and poor generalizability to different surface types [12]. To address these shortcomings, new research marries CNNs and transfer learning, data augmentation and domain adaptation (as shown in Figure 1). In addition to that, hybrid CNN-based models integrating conventional image processing and DL are promising in improving accuracy and flexibility.

B. Autoencoders (AE) and Variants

An autoencoder (AE) is a common DL model that is intended for unsupervised feature representation learning of data. Strong representation learning capacity, straightforward framework, and ease of training are among AE's benefits. In the field of FDD, it has been frequently employed. Additionally, a variety of AE-based variations have been created and used in the FDD area to get around different data qualities or to make the learnt feature representations show distinct beneficial aspects [13]. RNN and CNN are two examples of DL modules that may be used in lieu of the encoder-decoder framework's encoder and decoder parts to extract complicated data characteristics.

Specific AE Variants in Defect Detection:

- **Convolutional autoencoder (CAE):** These methods circumvent the computational expense disadvantage of picture denoising by presenting the problem inside the statistical framework of regression, which results in a more manageable calculation [14]. Therefore, compared to density estimation, they provide for more representational capacity.
- **Denoising Autoencoders (DAEs):** It is a unique kind of autoencoder that must learn the features in order to regenerate the complete samples from noisy inputs [15]. The suggested approach fixes the faulty PCBs in addition to identifying and locating potential flaws.
- **Memory-Augmented Autoencoders:** It was suggested to address the issue of partial defect reconstruction [16]. Memory-augmented autoencoder-based techniques frequently have trouble restoring complicated flaws and rely on restoring defects for inspection.

C. Generative Adversarial Networks (GANs)

GAN comprise a generator network and a discriminator network that are both taught through competition. The generator's job is to mimic the training data as precisely as possible, while the discriminator's is to tell the difference between the two. GANs may be specially trained with a focus on anomaly detection in order to produce examples from the minority class or the anomalies. By exposing the GANs to a balanced ratio of normal and anomalous events during training, they can learn to produce synthetic data that more precisely reflects both classes. Figure 2 illustrates the proposed Magna-Defect-GAN and a deep generative model where an image is encoded and combined with a latent noise vector, mask embedding, and guide vector. The decoder reconstructs a defect-enhanced output, aiding in anomaly detection or image restoration tasks.

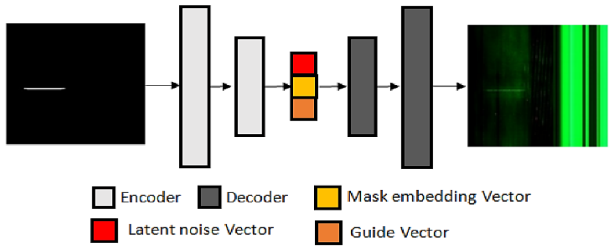

Fig. 2. Structure of the proposed Magna-Defect-GAN

How GANs are used in defect detection is as follows:

- **Data Augmentation:** A defect detection model's training dataset can be enhanced by creating synthetic pictures with GANs [17]. The training dataset may be made more diverse and the model's capacity for generalization enhanced by including synthetic images.
- **Unsupervised Anomaly Detection:** GANs are trained on defect-free images so that the generator learns to reconstruct only normal patterns. When an image with defects is passed through the generator, the defective regions are not accurately reconstructed, resulting in noticeable differences between the input and output [18]. These discrepancies, measured using residual computation methods, are quantified as anomaly scores to effectively identify and localize defects.

The two networks that make up the fundamental architecture of GANs pursue opposing optimization objectives with respect to a loss function. Combining the DiffAugment approach with the StyleGAN2 architecture.

- In terms of perceived picture quality and current distribution quality measures, StyleGAN2 is an enhanced GAN network.
- DiffAugment is a simple tool that increases GAN data efficiency by applying differentiable augmentations to both real and fake samples.

This combination improves convergence and stabilizes training, in contrast to other techniques that alter the distribution of real images by directly enriching the training data [19].

III. Applications, Domains, and Use Cases

In many different sectors, defect detection is essential to guaranteeing performance, safety, and dependability. The application of DL approaches has greatly improved the capacity to identify, categories, and pinpoint flaws in fields including healthcare, civil infrastructure, and industrial manufacture. These methods have outperformed conventional techniques by leveraging feature extraction, image classification, and anomaly detection capabilities. This section explores domain-specific applications, highlighting how AI-driven tools are revolutionizing structural monitoring, medical diagnostics, and automated inspection systems with greater accuracy and adaptability.

A. Defect Detection in Industrial Manufacturing

In general, a defect is described as an area or absence that deviates from a typical sample. A number of issues, such as subpar working conditions and insufficient technology, influence the quality of manufactured goods throughout the production process [20]. Defect identification used to be done by professionals. The significant impact of human subjectivity on the detection findings was one of the main causes of this. Much work has been spent on surface defect detection using conventional techniques. On the basis of the product's attributes, three conventional methods can be identified: those based on texture, colour, and shape.

Defect detection has seen DL's meteoric rise in popularity as a result of its ability to improve the efficiency and accuracy of the process. Specialized methods have been employed in a number of investigations to identify surface imperfections. Using a vector texture feature and a percentage of the colour histogram feature, the colour-based feature approach classifies picture blocks to identify surface flaws in wood [21]. Recent uses of ML-based vision algorithms to identify surface flaws in industrial items have been divided into three groups according to texture, colour, and form characteristics:

- **Texture-based:** Gray level co-occurrence matrix, Mathematical morphological, Fractal model, Gabor filter
- **Colour-based:** Bivariate colour histograms and colour coherence vectors are useful tools for identifying and locating flaws.
- **Shaped-based:** The use of Fourier spectra between the template and the inspection picture allows for a comparison of all the Defects, and it can find a range of non-repeating patterns in the electronics industry, even ones as little as one pixel wide.

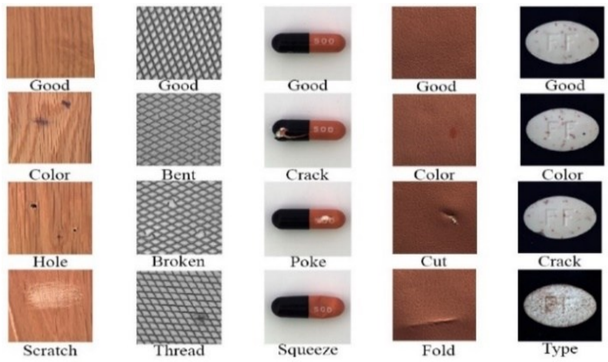

Fig. 3. Compares normal samples with defective samples of industrial products

Defective samples and normal samples of industrial goods are contrasted (as seen in Figure 3). The top row contains good samples, while the second, third, and fourth rows contain inferior samples. Below the image, three types of defects are listed; the first, second, third, and fourth columns display wood, grid, capsule, leather, and bill, in that order.

B. Infrastructure and Construction Monitoring

In order to evaluate the safety and integrity of civil infrastructure, structural health monitoring, or SHM, continually analyzes data from embedded sensors. The primary objectives of SHM systems are to monitor structural conditions, detect damage or anomalies, and evaluate long-term performance [22]. As a multidisciplinary and evolving technology, SHM enables intelligent maintenance strategies, contributing significantly to the modernization and sustainability of infrastructure systems [23]. Notably, ML techniques have been shown to offer trustworthy solutions to issues related to identifying infrastructure flaws, outperforming conventional techniques in the areas of precision, automation, speed, adaptability, and scalability.

One prominent example is the municipal drainage system, a critical yet often overlooked component of urban infrastructure. Closed-circuit television (CCTV) has become the standard for inspecting sewer networks. However, the vast volume of CCTV footage spanning thousands of kilometers of underground pipelines makes manual analysis labour-intensive and time-consuming, often requiring large teams of trained personnel [24]. In order to overcome this difficulty, deep learning-based frameworks have been suggested to enable real-time defect detection in an automated way. They collaborate the convolutional neural networks (CNNs) and other advanced models to detect the structural deformities in the sewer pipes directly based on CCTV images, which can save a lot of time on the inspection process and at the same time improve both the accuracy and the repeatability of the results collected.

C. Healthcare and Biomedical Imaging

Electronic health records (EHRs), computerized physician order entry (CPOE), and clinical decision support systems (CDSS) are current healthcare essentials [25]. Such systems simplify the work processes, minimize the number of medical errors, and improve patient outcomes by delivering the right information at the right time. Nonetheless, the importance of and the complexity of clinical software demand high requirements of the reliability and quality of the software. The impact of defects in this kind of software is very serious, and it may include the safety of patients, non-conformity to regulatory standards, and significant financial losses.

Their conventional fault-finding methods, such as manual reviews of code and standard rule-based static analysis, are not always reliable for detecting subtle and context-sensitive faults in clinical apps, in most situations. This limitation is compounded by the intricate dependencies, domain-specific logic, and frequent updates characteristic of healthcare software [21]. To address these challenges, predictive defect detection methods using machine learning have gained traction, enabling the early identification of high-risk modules based on historical data and software metrics.

The model-based methods detect faults in photos with little to no variance. Since there are a variety of uncertainties in industrial settings about the severity of errors in their forms and sizes, it is essential to create techniques that can adjust to these vast variances. Because learning-based approaches are more resilient to variance, they offer a superior substitute for preprogrammed feature identification techniques. Such resilience is possible with traditional ML techniques for regression and classification. These learning-based approaches make use of NN, DT, KNN, SVM, and NB. These methods train the expected faults by taking into account the statistical variability of the defects on the images.

IV. Challenges and Future Research Directions

Even though significant improvements have been achieved in the field of DL in defect detection, there are several urgent issues that prevent its large-scale use in industry. The critical issues range between data-related challenges, including data imbalance, the complexity of annotations and data quality, generalization and model robustness issues and the increased need to explain the predictions and to trust them. Such issues limit both model performance and scalability, as well as reliability and user adoption. These barriers need to be solved in order to make defect detection systems resilient, transparent, and adaptable. This part is critical about these limitations as well as stating possible ways of future research to mitigate these and increase efficiency of the systems as including:

A. Data Challenges: Imbalance, Annotation, and Quality

One of the biggest obstacles to developing reliable and transferable DL models for defect identification is the amount of data that is currently available. One of the biggest issues is class imbalance, which occurs when there are more normal samples than defective ones. Models' sensitivity and reliability in real-world applications might be compromised due to imbalanced representations caused by this class imbalance, which fail to detect infrequent but critical errors.

The next obstacle is the complexity of the annotation. Specific knowledge of the domain is usually necessary to create good labels on type of defects, which makes the annotation task error-prone, resource-intensive, and time-consuming. Additionally, inconsistencies in labelling across different datasets introduce noise, which adversely affects the training process and diminishes the model's robustness and generalization capability [26].

The quality of training data is equally vital, especially in applications like sewer or infrastructure defect detection, where CNN-based models rely heavily on the fidelity and representativeness of input data. Poor image resolution, occlusions, and environmental variability can degrade model performance [27]. To address these issues effectively, several steps are recommended.

- It is especially important to examine the associated data errors.
- To specify the necessary steps for removing the mistake sources and cleaning up the inaccurate data.
- Prioritize the different data mistakes, take the appropriate action, and move them to the appropriate project plan.

Overall, addressing these data-centric issues is foundational for building scalable and reliable deep learning systems for defect detection in diverse industrial contexts.

B. Generalization and Model Robustness

Models can learn concepts instead of exact rules thanks to DL's generalization capabilities. As an example, classifiers that have been trained on ImageNet's 14 million pictures can anticipate which subjects belong to which classes in unfamiliar settings. The goal of training a model to generalize is not to find laws but rather to teach it broad ideas about what makes one type of object different from another, such as a bird from an aeroplane. When inspecting for defects, it is common for the background image to be the same, and the defects themselves may be similar in type or location. These cases increase the likelihood that models will learn shortcuts that are either unrelated to the picture defect or do not apply to newly discovered faults [28]. This study utilizes a dataset that incorporates a diverse array of external data, including fault types applicable in various contexts, to train a machine learning model that addresses the over-fitting problem in defect inspection.

- In order to enhance model generalization, data augmentation techniques, including flips, rotations, and color modifications, have been used to artificially increase the variety of training data.
- Adversarial assaults, in which models are susceptible to inputs that are purposefully altered to produce mistakes.
- Adversarial training has been implemented. To increase resilience against these disturbances, this method trains models on synthetic adversarial cases.

C. Explainability and Trustworthiness

Explainable Artificial Intelligence (XAI) sought to increase machine learning models' interpretability, transparency, and understandability in order to foster confidence in AI systems and guarantee that judgments made by AI could be rationalized and explained. Different approaches can be taken to improve the machine learning model's explainability; the choice depends on the data, the type of explanation, and the ML algorithm used:

- A method for determining the relative significance of each feature in a machine learning model is called permutation feature importance. It reveals the extent to which the performance of a model would be affected by randomly shuffling the values of a specific feature while keeping the values of other features constant.
- LIME is a method for explaining specific predictions that ML models make. It aspires to shed light on the "black box" component of numerous complex models.

LIME provides an instance-specific local explanation for "Trusting a prediction" by determining which input data aspects significantly impact the prediction's outcome [29]. A glass model, which is a simple and interpretable model, is created by LIME to mimic the behaviour of the sophisticated model locally around the instance of interest. This model takes linear regression as an example.

D. Future Directions

Despite significant progress in DL-based material defect detection, current approaches still struggle to meet the demanding requirements of practical industrial applications, particularly in terms of cost-effectiveness, scalability, robustness, and real-time performance. Many systems find it difficult to maintain consistent performance across a variety of operational settings, although contemporary machine learning algorithms have greatly increased detection accuracy. The creation of flexible, interpretable, and resource-efficient models should be the main goal of future research in order to overcome these difficulties. To advance defect detection technology towards dependable and scalable industrial deployment, this section lists the main obstacles and possible paths forward. Additionally, in order to better reflect real-world fault scenarios, emphasis should be placed on developing vast, diversified, and high-quality datasets. Furthermore, combining domain expertise with learning informed by physics may improve model generalization and usefulness.

V. Literature Review

This section reviews recent studies on DL approaches for defect detection, focusing on segmentation, generative models, and hybrid architectures. Table I summarizes each study's methodology, key contributions, limitations, and future directions, offering insights into scalable, accurate, and efficient detection systems.

Rahman et al. (2025) provide a thorough analysis that fills this gap by combining state-of-the-art DL approaches with conventional segmentation techniques. As AI advances, especially in picture segmentation, it challenges the efficiency and accuracy of traditional human inspection methods. This article provides a comprehensive study of methodological improvements, application breadth, and developing trends. The integration of hybrid techniques, DL models, and innovations like lightweight structures and attention mechanisms is emphasized. To improve model scalability, robustness, and flexibility, the analysis also identifies important research issues and suggests future lines of inquiry. This systematic study is a crucial resource for defect identification using image segmentation, as it fills in knowledge gaps and offers practical insights for both academia and industry [30].

Kohli and Chhabra (2025) describe the function of DL approaches in outlier classification and feature extraction across application areas. DL technologies have become a viable substitute for traditional ML techniques because of their ability to model features, evaluate detection rates, and mimic cognitive growth. The most recent experimental research methods and standard datasets are thoroughly examined. The methods used, performance metrics, datasets, difficulties encountered, and application areas all demonstrate the scholarly achievements over the last ten years. The study concludes by outlining the necessity for hybrid models, cutting-edge technology, and enhanced interpretability as future research avenues [31].

He et al. (2024) provide a comprehensive review of the current literature on surface defect inspection methods proposed for the years 2022–2024. To begin, these methods can be categorized into four sets, each with its own focus on generative models: multi-models, generative adversarial networks (GANs), diffusion models (DMs), and variational auto-encoders (VAEs). Part two delves into the current landscape of generative model surface defect inspection research from four angles: learning model, inspection problem, detection aim, and sample production. Presenting a comparative comparison of generative model-based defect inspection techniques follows, followed by a discussion of the available datasets and evaluation criteria commonly used for surface defect assessment. The paper finishes by discussing the challenges that generative model-based defect inspection systems are now facing and by proposing areas for further research [32].

Ma et al. (2024) provide a comprehensive overview of the development of industrial defect detection methods based on supervised and unsupervised algorithms, address critical difficulties, and outline future possibilities. Additionally, it contains evaluation metrics and standard datasets utilized for industrial product defect detection. To overcome these obstacles and improve fault detection, several strategies have been put forth. to thoroughly examine the most recent advancements in industrial product fault detection methods based on DL. It draws attention to the possibility of enhancing defect detection systems' precision, speed, and dependability in industrial settings. Using DL-based object detection algorithms is one of the main goals of industrial product fault detection [33].

Jiang et al. (2023) provide a transformer network for surface defect segmentation that uses multi-stage CNN feature insertion. This structure is similar to UNet and is called CIN Former. Efficiently and simply, CINFormer provides a feature integration method that incorporates the input picture's multi-level CNN characteristics into the encoder's transformer network at different levels. This can preserve the advantages of CNN's ability to capture fine details and the transformer's ability to suppress background noise, both of which help with precise fault identification. Additionally, CIN Former provides a Top-K self-attention module that zeroes in on tokens that provide more critical information regarding the defects, thereby mitigating the impact of the duplicated backdrop. Trials on the surface defect datasets DAGM 2007, Magnetic tile, and NEU show that the proposed CIN Former performs at a state-of-the-art level when it comes to defect identification [34].

Wang et al. (2023) The Defect Transformer (DefT), a successful hybrid transformer design for surface defect detection, which uses convolutional neural networks (CNNs) and transformers as one model to capture both local and non-local interactions. To be more specific, the encoder module employs a convolutional stem block to initially store more complex spatial information. After that, they use the patch aggregation blocks to make a multi-scale representation with four levels of hierarchy. After each of these blocks, there is a series of DefT blocks. These blocks help with feature transformation and learning more location information, model multi-scale global contextual relationships with good computational efficiency, and encode local positions. Another block uses a lightweight multi-pooling self-attention. They conclude with a simple yet effective decoder module that gradually recovers spatial data from the encoder's skip connections [35].

Table I summarizes key studies on deep learning-based defect detection, outlining model types, application domains, datasets used, evaluation metrics, and performance outcomes, while also highlighting existing limitations and future research directions for improved defect identification accuracy.

TABLE I. COMPARATIVE ANALYSIS OF RECENT STUDIES ON DEEP LEARNING-BASED DEFECT DETECTION TECHNIQUES

Reference	Study On	Approach	Key Findings	Challenges	Future Direction
Rahman et al. (2025)	Image segmentation for defect detection	Systematic review integrating deep learning models, hybrid techniques, and lightweight architectures	Holistic coverage of methods, datasets, and trends in segmentation-based fault detection	Scalability and adaptability of models	Enhance robustness, develop generalizable segmentation frameworks
Kohli et.al. (2025)	Outlier classification using deep learning	Comparative review of DL-based feature extraction and classification	DL outperforms classical ML in feature learning and detection accuracy	Hardware constraints, interpretability issues	Develop hybrid models, focus on efficient and explainable AI
He et al. (2024)	Surface defect detection with generative models	Review of VAE, GAN, Diffusion, and multi-model-based inspection systems	Categorized and evaluated inspection models based on learning type and dataset use	Lack of robust learning with limited defect samples	Improve generalization, refine multi-model fusion approaches
Ma et al. (2024)	Industrial product defect detection	Survey on supervised/unsupervised object detection algorithms	Comprehensive trace of one-stage, two-stage, and unsupervised DL models	High variance in accuracy across datasets and conditions	Boost speed and reliability; leverage domain adaptation
Jiang et al. (2023)	Surface defect segmentation (CINFormer)	CNN-transformer hybrid with Top-K self-attention	Preserves spatial detail, suppresses background noise for improved accuracy	Balancing CNN-local and transformer-global features	Broaden dataset applicability, enhance real-time deployment
Wang et al. (2023)	Surface defect detection (DefT)	Hybrid architecture combining CNN and transformer blocks	Achieves fine-grained spatial encoding with multi-scale global context	Complexity in encoder-decoder integration	Design lightweight, energy-efficient detection architectures

VI. CONCLUSION AND FUTURE WORK

Exploring the evolution of DL in defect detection reveals both significant progress and pressing limitations. Across industrial domains, the integration of CNNs, GANs, and hybrid DL models has elevated detection accuracy, yet key technical and data-related challenges continue to hinder broader adoption. Drawing from a wide spectrum of recent developments, this review highlights how DL algorithms have transformed defect detection tasks by enabling high precision and automation. Although the current state is very impressive, there are still concerns with data imbalance, generalization gaps, and model explainability. To address these difficulties, it will be necessary to use high-quality data, novel training practices, and understandable AI practices. Also, the application to industry is to be increased with the emphasis on future studies on domain adaptation, real-time inference, and trust-building mechanisms. With the growth of industries in the direction of intelligent automation, DL will continue to play a role in defect detection as long as the existing limitations are methodically resolved with interdisciplinary innovation and strict validation. Such a balance between being accurate, reliable and interpretable determines the future path.

Future research should concentrate on making accurate, interpretable, and generalizable DL models that can be applied to a wide range of defect types on different materials. It is necessary to focus on the development of high-quality and scale-annotated datasets and an enhanced real-time detection capability. Furthermore, the approach that combines lightweight networks, domain adaptation, and explainable AI techniques can contribute to increased transparency of the model and its industrial deployment and pave the way for more intelligent and scalable defect detection systems.

REFERENCES

[1] V. Rajavel, "Novel Machine Learning Approach for Defect Detection in DFT Processes," *Am. Sci. Res. J. Eng. Technol. Sci.*, vol. 101, no. 1, pp. 325–334, 2025.

[2] S. Talebi, S. Wu, A. Sen, N. Zakizadeh, Q. Sun, and J. Lai, "Infrastructure automated defect detection with machine learning: a systematic review," *Int. J. Constr. Manag.*, pp. 1–12, Apr. 2025, doi: 10.1080/15623599.2025.2491622.

[3] V. Rajavel and R. Gahlot, "Advanced Fault Diagnosis of CMOS Circuit Design by Leakage Measurement in Nanometer Technology," in *2025 IEEE 5th International Conference on VLSI Systems, Architecture, Technology and Applications (VLSI SATA)*, IEEE, May 2025, pp. 1–6. doi: 10.1109/VLSISATA65374.2025.11070065.

[4] R. Ameri, C. C. Hsu, and S. S. Band, "A systematic review of deep learning approaches for surface defect detection in industrial applications," *Eng. Appl. Artif. Intell.*, vol. 130, Apr. 2024, doi: 10.1016/j.engappai.2023.107717.

[5] S. Nokhwal, P. Chilakalapudi, P. Donekal, S. Nokhwal, S. Pahune, and A. Chaudhary, "Accelerating Neural Network Training: A Brief Review," in *2024 8th International Conference on Intelligent Systems Metaheuristics & Swarm Intelligence (ISMSI)*, New York, NY, USA: ACM, Apr. 2024, pp. 31–35. doi: 10.1145/3665065.3665071.

[6] K. Weiher *et al.*, "Automated Visual Inspection of Manufactured Parts using Deep Convolutional Neural Networks and Transfer Learning," *Procedia CIRP*, vol. 120, pp. 858–863, 2023, doi: 10.1016/j.procir.2023.09.088.

[7] N. Nikolakis, P. Catti, L. Fabbro, and K. Alexopoulos, "Adapting Vision Transformers for Cross-Product Defect Detection in Manufacturing," *Procedia Comput. Sci.*, vol. 253, pp. 2693–2702, 2025, doi: 10.1016/j.procs.2025.01.329.

[8] H. Kali, "The Future of HR Cybersecurity: AI-Enabled Anomaly Detection in Workday Security," *Int. J. Recent Technol. Sci. Manag.*, vol. 8, no. 6, pp. 80–88, 2023.

[9] V. Thangaraju, "Enhancing Web Application Performance and Security Using AI-Driven Anomaly Detection and Optimization Techniques," *Int. Res. J. Innov. Eng. Technol.*, vol. 9, no. 3, 2025, doi: 10.47001/IRJIET/2025.903027.

[10] R. Yamashita, M. Nishio, R. K. G. Do, and K. Togashi, "Convolutional neural networks: an overview and application in radiology," *Insights Imaging*, vol. 9, no. 4, pp. 611–629, 2018, doi: 10.1007/s13244-018-0639-9.

[11] K. S, V. T, A. S, G. D.J, A. K, and S. Madhumitha, "Comparative Analysis of CNN-based Feature Extraction Techniques and Conventional Machine Learning Models for Quality Assessment in Agricultural Produce," *SSRN Electron. J.*, 2025, doi: 10.2139/ssrn.5089073.

[12] M. Swapna, Y. K. Sharma, and B. Prasad, "CNN Architectures: Alex Net, Le Net, VGG, Google Net, Res Net," *Int. J. Recent Technol. Eng.*, vol. 8, no. 6, pp. 953–959, Mar. 2020, doi: 10.35940/ijrte.F9532.038620.

[13] J. Qian, Z. Song, Y. Yao, Z. Zhu, and X. Zhang, "A review on autoencoder-based representation learning for fault detection and diagnosis in industrial processes," *Chemom. Intell. Lab. Syst.*, vol. 231, p. 104711, Dec. 2022, doi: 10.1016/j.chemolab.2022.104711.

[14] E. Pintelas, I. E. Livieris, and P. E. Pintelas, "A Convolutional Autoencoder Topology for Classification in High-Dimensional Noisy Image Datasets," *Sensors*, vol. 21, no. 22, Nov. 2021, doi: 10.3390/s21227731.

[15] S. Khalilian, Y. Hallaj, A. Balouchestani, H. Karshenas, and A. Mohammadi, "PCB Defect Detection Using Denoising Convolutional Autoencoders," in *2020 International Conference on Machine Vision and Image Processing (MVIP)*, IEEE, Feb. 2020, pp. 1–5. doi: 10.1109/MVIP49855.2020.9187485.

[16] T. G. Shiferaw and L. Yao, "Autoencoder-Based Unsupervised Surface Defect Detection Using Two-Stage Training," *J. Imaging*, vol. 10, no. 5, May 2024, doi: 10.3390/jimaging10050111.

[17] V. Sampath, I. Maurtua, J. J. A. Martín, A. Iriondo, I. Lluvia, and G. Aizpurua, "Intraclass Image Augmentation for Defect Detection Using Generative Adversarial Neural Networks," *Sensors*, vol. 23, no. 4, Feb. 2023, doi: 10.3390/s23041861.

[18] Y. Wang, Y. Zhang, L. Zheng, L. Yin, J. Chen, and J. Lu, "Unsupervised Learning with Generative Adversarial Network for Automatic Tire Defect Detection from X-ray Images," *Sensors*, vol. 21, no. 20, Oct. 2021, doi: 10.3390/s21206773.

[19] F. A. Saiz, G. Alfaro, I. Barandiaran, and M. Graña, "Generative Adversarial Networks to Improve the Robustness of Visual Defect Segmentation by Semantic Networks in Manufacturing Components," *Appl. Sci.*, vol. 11, no. 14, Jul. 2021, doi: 10.3390/app11146368.

[20] S. Garg, "AI-Driven Innovations in Storage Quality Assurance and Manufacturing Optimization," *Int. J. Multidiscip. Res. Growth Eval.*, vol. 1, no. 1, pp. 143–147, 2020, doi: 10.54660/.IJMRGE.2020.1.1.143-147.

[21] A. Saberironaghi, J. Ren, and M. El-Gindy, "Defect Detection Methods for Industrial Products Using Deep Learning Techniques: A Review," *Algorithms*, vol. 16, no. 2, Feb. 2023, doi: 10.3390/a16020095.

[22] N. Malali, "View of Real-Time Liability Monitoring in Annuities Using Actuarial Dashboards on Streaming Data," *Asian J. Comput. Sci. Eng.*, vol. 8, no. 1, pp. 1–7, 2023.

[23] X. W. Ye, J. Tao, and C. B. Yun, "A review on deep learning-based structural health monitoring of civil infrastructures," *Smart Struct. Syst.*, vol. 24, pp. 567–585, 2019, doi: 10.12989/sss.2019.24.5.567.

[24] X. Yin, Y. Chen, A. Bouferguene, H. Zaman, M. Al-Hussein, and L. Kurach, "A deep learning-based framework for an automated defect detection system for sewer pipes," *Autom. Constr.*, vol. 109, Jan. 2020, doi: 10.1016/j.autcon.2019.102967.

[25] M. A. Mostafiz, "Machine Learning for Early Cancer Detection and Classification: AIBased Medical Imaging Analysis in Healthcare," *Int. J. Curr. Eng. Technol.*, vol. 15, no. 03, pp. 1–10, 2025.

[26] M. H. Yorulmuş, H. B. Bolat, and Ç. Bahadır, "Predictive Quality Defect Detection Using Machine Learning Algorithms: A Case Study from Automobile Industry," in *INFUS 2021: Intelligent and Fuzzy Techniques for Emerging Conditions and Digital Transformation*, 2022, pp. 263–270. doi: 10.1007/978-3-030-85577-2_31.

[27] O. Azeroual, G. Saake, and M. Abuosba, "Data Quality Measures and Data Cleansing for Research Information Systems," *J. Digit. Inf. Manag.*, vol. 16, no. 1, pp. 12–21, 2018.

[28] A. M. Mezher and A. E. Marble, "A Novel Strategy for Improving Robustness in Computer Vision Manufacturing Defect Detection," pp. 1–25, 2023.

[29] H. Bordekar, N. Cersullo, M. Brysch, J. Philipp, and C. Hühne, "eXplainable artificial intelligence for automatic defect detection in additively manufactured parts using CT scan analysis," *J. Intell. Manuf.*, vol. 36, no. 2, pp. 957–974, Feb. 2025, doi: 10.1007/s10845-023-02272-4.

[30] M. M. Rahman, S. Rahman, S. Bhatt, and M. Faezipour, "A Systematic Review on Advancement of Image Segmentation Techniques for Fault Detection Opportunities and Challenges," *Electronics*, vol. 14, no. 5, Feb. 2025, doi: 10.3390/electronics14050974.

[31] M. Kohli and I. Chhabra, "A comprehensive survey on techniques, challenges, evaluation metrics and applications of deep learning models for anomaly detection," *Discov. Appl. Sci.*, vol. 7, no. 7, p. 784, Jul. 2025, doi: 10.1007/s42452-025-07312-7.

[32] Y. He, S. Li, X. Wen, and J. Xu, "A Survey on Surface Defect Inspection Based on Generative Models in Manufacturing," *Appl. Sci.*, vol. 14, no. 15, Aug. 2024, doi: 10.3390/app14156774.

[33] Y. Ma, J. Yin, F. Huang, and Q. Li, "Surface defect inspection of industrial products with object detection deep networks: a systematic review," *Artif. Intell. Rev.*, vol. 57, no. 12, Oct. 2024, doi: 10.1007/s10462-024-10956-3.

[34] X. Jiang *et al.*, "CINFormer: Transformer network with multi-stage CNN feature injection for surface defect segmentation," vol. 20, pp. 1–10, 2023.

[35] J. Wang, G. Xu, F. Yan, J. Wang, and Z. Wang, "Defect transformer: An efficient hybrid transformer architecture for surface defect detection," *Measurement*, vol. 211, no. 8, Apr. 2023, doi: 10.1016/j.measurement.2023.112614.

