IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 12 May 2023, accepted 25 May 2023, date of publication 29 May 2023, date of current version 5 June 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3280992

TOPICAL REVIEW

Aero-Engine Blade Defect Detection: A Systematic Review of Deep Learning Models

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This work was supported by the Advanced Research and Innovation Center (ARIC) funded in part by Sanad (a Mubadala company), and in part by the Khalifa University of Science and Technology.

ABSTRACT Aero-engine blade defect detection is a crucial task in ensuring the safety and reliability of aircraft. The visual inspection of aero-engine blades is a complex process that requires extensive knowledge and experience. This paper presents a systematic literature review (SLR) of deep learning models for detecting defects in aero-engine blades. The review considers 13 primary studies, including methods and conceptual works. This is the first systematic review of deep learning models for aero-engine blade defect detection. The findings of this review demonstrate the potential of deep learning in detecting blade defects and improving the accuracy and efficiency of visual inspection. However, there is a need for more research on integrating deep learning models into practical applications and developing robust and reliable systems for defect detection. This review framework provides a comprehensive methodology for selecting and evaluating relevant studies, which researchers can use for future investigations in this area. These results should encourage further work on deep learning techniques, system integration, and testing and validation for defect detection of aero-engine blades.

INDEX TERMS Systematic literature review (SLR), defect detection, computer vision, aero-engine blade, deep learning.

I. INTRODUCTION

The aero-engine blade is a critical component of any aircraft engine, as it is exposed to some of the harshest operating environments in terms of temperature and pressure while operating at extremely high speeds [1]. Adequate and reliable inspection of aero-engine blades is an integral part of the manufacturing, maintenance, and repair processes, considering that any defect on the blade can result in the engine shutting down, causing incidents [2]. Ensuring that aero-engine blades from the production line are high quality and without significant defects is essential to manufacturing. Even though the manufacturing, maintenance, and repair processes have significantly improved over the years, it is still challenging to detect minor defects of the size of 1 mm or smaller [3]. These small defects continue to present a considerable threat to the safe operation of airplanes. In this regard, various techniques and methodologies are continuously being developed to automate the defect detection process in aero-engine blades.

Several non-destructive inspection techniques have been used to perform the aero-engine blade inspection process. This includes eddy current testing [4], ultrasonic testing [5], magnetic testing of particles [6], and radiography [7]. These techniques have proven useful in internal aero-engine blade defect detection. However, detecting surface defects is often left to highly experienced inspectors making the entire process highly inefficient and limited to subjective individual judgments [3]. Additionally, even highly experienced inspectors often miss minute defects. Blade inspection can be divided into in-situ borescope inspection and module and

The associate editor coordinating the review of this manuscript and approving it for publication was Antonio J. R. Neves.

piece-part inspection. In-situ borescope inspection involves inspecting the aircraft engine while it is still assembled, while module and piece-part inspection involves disassembling the aircraft engine and inspecting each component individually.

Deep learning models have great potential in industrial applications, including defect detection, quality control, predictive maintenance, and process optimization [8]. With the increasing availability of data and advancements in computing power, deep learning has become essential for improving efficiency, reducing costs, and enhancing productivity in industrial settings. In the context of defect detection, deep learning models have demonstrated high levels of accuracy in detecting various types of defects, including surface defects, cracks, and anomalies [9], [10], [11], [12]. These models can analyze large amounts of data from different sources, including images, videos, and sensor data, to detect and classify defects automatically. By automating the detection process, deep learning models can help reduce the time and cost of manual inspections and improve the consistency and reliability of defect detection [13]. Recently, Computer vision-driven approaches coupled with deep learning have emerged as effective and efficient defect detection techniques for various industrial applications such as quality control, predictive maintenance, and process optimization [14], [15], [16], [17]. Multiple experimental studies continue to report high levels of accuracy in metal surface defect detection via computer vision and deep learning [18], [19], [20], [21], [22].

However, applying these methods directly to aero-engine blade defect detection poses several challenges. Due to these challenges, little work has been done investigating aero-engine blades. Most existing research in defect detection has focused on other industries. The small size of defects, higher precision requirements, and the complex geometries of the blades make it challenging to apply the same techniques used in other industries. Additionally, the detection of blade defects requires a higher level of precision and accuracy due to the criticality of the component in ensuring aircraft safety [3].

Despite the challenges, blade defect detection has been a topic of interest in many recent publications, with different methods being explored and reporting varying levels of precision. These methods include traditional machine learning algorithms and deep learning models [23]. One of the main advantages of deep learning models is their ability to automatically extract representative features from blade images to distinguish between different types of defects, improving the efficiency and accuracy of aero engine blade defect detection. By training on a wide range of images, the models can learn to recognize patterns and features indicative of blade damage, reducing the risk of missed defects and increasing detection speed. The ability of deep learning models to automatically extract and recognize features makes them a valuable tool for improving blade defect detection in the aviation industry.

This paper explores recent studies on the rapidly emerging and maturing technologies and methodologies of aero-engine blade inspection. It undertakes a systematic literature review comparing and contrasting methods, technologies, and performance outcomes. This review aims to assist researchers and engineers in finding, evaluating, and understanding the most important research papers on using deep learning to inspect aero-engine blades.

In the context of emerging capabilities and challenges with the use of computer vision and non-computer vision in the detection of aero-blade defects, the objectives of this systematic literature review are to:

1) Explore how deep learning models are adapted to detect aero-engine blade surface defects.
2) Identify current challenges that face the adoption of deep learning models in the field of aero-engine blade inspection.

The remainder of this paper is organized as follows. Section II summarizes the background and the related work. Section III describes the methodology. Section IV explains and presents the qualitative results of the study. Section V concludes by summarizing the findings.

II. BACKGROUND AND RELATED WORKS

A. BACKGROUND

The integrity of the blades is a vital part of an aircraft's overall health. If a blade is defective or damaged, it can lead to inflight shutdowns and engine failure. Identifying the damage to the blades is one of the most crucial factors that can affect an engine's health [24]. The turbine and compressor blades are responsible for the majority of aircraft failures. According to the International Air Transport Association (IATA), aircraft inspection and maintenance errors are among the primary causes of aircraft accidents. The Federal Aviation Authority (FAA) also reported that 6.8% of accidents and 27.4% of fatalities are caused by maintenance errors [2]. Although it is not always possible to provide statistics on the exact number of incidents involving blade damage, the FAA noted that from 2008 to 2018, there were several reports of engine malfunctions or failures in the US. The recent incidents have highlighted the need for regular and thorough blade inspections to prevent accidents and enhance the safety of the passengers and crew [25]. Aero-engine blade damages are categorized based on type, impact, causes, location, repairability, and frequency of occurrence. Damage types range from natural tear and wear, surface damages, deforming materials, and joinery separations [24]. Damages can also be classified based on mechanical, thermal, and chemical influences [26]. The impact of damage on aero-engine blades, such as diminished fatigue resistance, engine explosions, engine stall, and high fuel consumption occasioned by diminished efficiency and airflow, are also used to classify blade damages [24]. Table 1 highlights attributes that classify aero-engine blade damages. Moreover, understanding damage types influences the choice of tools and approaches in damage inspection. Figure 1 visualizes some common blade defects that can be detected through deep-learning computer vision models.

Table 2 provides an overview of the common types of defects, including corrosion, cracks, breaking, neck, tear,

TABLE 1. Classification of aero-engine blade damages.

No.	Criterion	Description
1	Damage Types	Deformation and separation of material, natural tear and wear [24].
2	Effect	Chemical, thermal, and mechanical [26].
3	Source	Production failures, operational failures, inadequate repair [27].
4	Impact	Diminished resistance to fatigue, engine failure [27].
5	Location	Blade side (concave or convex), blade edge (tails or leads), blade zones (A,B,C) [24], Surface damages (oxidation, cracks, and corrosion), internal microstructure damage (grain growth, rafting, carbide precipitation, and creep voiding amongst others) [28].
6	Repairability	Non-repairable and serviceable.
7	Detectability	Testing technology required, level of disassembly required [24].
8	Extent of damage	Allowable damage, routine damage detectable from regular inspections, discrete damage, and severe damage [29].

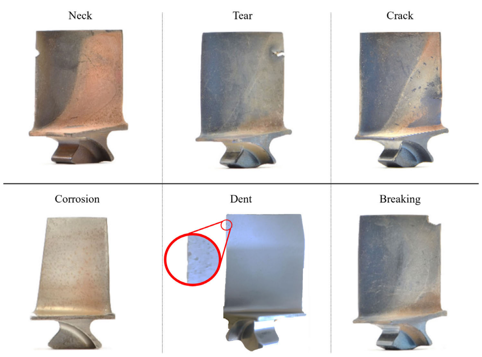

FIGURE 1. Images of different types of blade defects that can be detected through deep learning computer vision models [30].

and dent. The table includes brief descriptions and critical characteristics of each defect, such as the materials most susceptible to corrosion, the depth of cracks, and the visible features of necks and dents. With this knowledge, professionals can proactively identify and prevent these defects, ensuring optimal engine performance and safety. Furthermore, the information presented in the table can be used to develop effective strategies for mitigating the effects of these defects, thus extending the lifespan of the aero engine and ensuring its long-term reliability.

Ensuring damage tolerance is critical when inspecting aero-engine surfaces and blades. This involves identifying the specific locations of any damage, which is accomplished through a visual inspection using the available tools in the workshop. The inspection criteria outline the critical areas of each component, and while there is no one-size-fits-all approach, the provided manual for each blade set must be followed. By prioritizing damage tolerance, manufacturers and airlines can ensure the safety and reliability of their engines [30], [31].

To ensure the safety and reliability of their aircraft engines, airlines, aircraft manufacturers, and MRO companies use various techniques to inspect and detect surface damage and blade deterioration. These include visual inspection, eddy current, ultrasonic testing, and non-destructive methods. One of the essential hardware tools that operators use when carrying out visual inspection is a borescope, which can be used to inspect the inner part of an engine without taking apart the component [32].

A flexible fiber optic probe is used for borescope inspection. It contains a camera and light source, which allow the operator to inspect the insides of the engine and its blades. The engine will be run at low or idle power during the inspection. The operator slowly moves this probe through the various sections of the engine while the light source and camera are focused on the insides. This approach allows for a detailed examination of the various components of an engine, such as the turbine section and combustion chamber. The operator can also change the magnification and lighting settings to get a more complete view of the blades. The inspection of the blades of an engine is critical in maintaining the aircraft's safety and reliability [33].

TABLE 2. Common aero engines defects [24], [32], and [34].

Damage Type	Description	Characteristics
Corrosion	The gradual deterioration of a component's coating or surface due to an electrochemical or chemical reaction caused by exposure to hot or atmospheric gases in the working environment.	Corrosion can cause changes in the color, texture, and surface of the affected material, often resulting in a rough or pitted surface, High-strength stainless steel and aluminum components can corrode under the stress of tensile stresses.
Crack	A partial or material separation that can be visibly detected and lead to material breakage.	The depth of a component can vary from just a couple thousandths of its actual thickness to its full length. This can lead to the part being completely broken apart. This usually happens when the part's pre-existing defects are expanded.
Breaking	The process of a blade being separated into two or more large pieces due to external or internal stresses or forces acting upon it.	A loss of blade material. Usually caused by overtemperature and collision of external objects.
Nick	A small and sharp cut on the component's surface or edge, which is usually caused by an impact from a foreign object.	The bottom is typically V-shaped. The sides are dim, while the bottom is bright.
Tear	The separation of materials occurs when a sharp object causes tensile stresses to be exerted on them.	It typically accompanies the formation of cracks and results from the impact of external objects.
Dent	A type of damage or indentation that occurs on the surface of an object, typically caused by an impact or pressure from an external object.	Appear as small, smooth indentations with rounded corners, edges, and bottom.

B. DEFINITIONS

CNN (Convolutional Neural Network): An artificial neural network commonly used in computer vision tasks such as image classification and object detection. CNNs are designed to automatically identify and extract important features from images by applying a series of convolutional filters. This allows them to identify patterns and shapes in the image relevant to the task at hand [35].

FPNs (Feature Pyramid Networks): are a type of CNN designed to extract features at multiple scales. FPNs combine feature maps from multiple layers of the CNN to produce a pyramid of features, with higher-level features containing more abstract information [36].

RCNN (Regional Convolutional Neural Network): An object detection algorithm that generates region proposals in an image and then classifies each proposal using a CNN [37].

Mask RCNN: An extension of the RCNN algorithm that also predicts segmentation masks for each object in an image. This allows it to perform object detection and instance segmentation [37].

YOLO (You Only Look Once): A popular algorithm for detecting objects that uses a single-stage deep neural network to predict bounding boxes and class probabilities for objects in an image. YOLO is known for its fast processing speed and accuracy and has been widely used in real-time object detection applications [38], [39].

Transformers: A type of neural network architecture commonly used in natural language processing tasks but has also been adapted for computer vision. Transformers use self-attention mechanisms to capture long-range dependencies in the input data, making them well-suited for tasks such as image captioning and video analysis [40].

GCNN (Graph Convolutional Neural Network): A neural network that works with graph-structured data, such as social networks or molecular structures. Graph CNNs use convolutional filters to aggregate information from neighboring nodes in the graph, allowing them to identify patterns and structures in the data [41].

Ensemble learning: A technique that involves combining multiple models to improve prediction accuracy. In computer vision, ensemble learning can combine the output of multiple object detection or classification models to improve overall performance [42].

GAN (Generative Adversarial Network): A category of deep neural network used for generating new samples that resemble the original training samples. GANs consist of two networks - a generator network that creates new data and a discriminator network that distinguishes generated data from real data. The generator network learns to create new data indistinguishable from real data through training and feedback. In computer vision, GANs can be used for tasks such as generating images or enhancing low-resolution images [43].

C. RELATED WORKS

This section introduces relevant works related to this systematic review of deep-learning models for detecting defects in aero-engine blades. While there are a few review papers on inspecting aircraft, the literature lacks comprehensive reports that review the use of deep learning to inspect aero-engine blades. To address this gap, we included several papers in this review, presented in more detail in Section IV. The insufficient research on the development and status of deep learning-based inspection systems for aero-engine blades highlights the importance of conducting this systematic review and advocates for further research in this area.

Yasuda et al. [23] conducted a systematic literature review on methods and techniques used in the visual inspection of aircraft, including insights into the automation of these processes with robotics and computer vision. The review revealed a promising opportunity to automate and improve visual inspection techniques but also highlighted issues related to inadequate testing and validation of solutions, insufficient consideration for complete intelligent inspection systems, and inadequate requirement specifications in the literature. The authors concluded that the technology is still at an early stage of development with a low level of technological readiness, which poses a barrier to adoption in the aviation industry.

Lafiosca et al. [44] explored the feasibility of automating aircraft inspections, particularly through non-contact visual inspection methods. A qualitative comparison of different non-contact inspection methods for detecting various damage types is provided, and the best options for each are discussed. It is concluded that introducing automation in inspections can significantly reduce costs and increase reliability, but challenges remain, such as the lack of quality damage datasets for training AI algorithms. The best way forward is a combination of different non-contact methods with high volumes of quality data to train AI algorithms. Zou et al. [6] briefly summarized several non-destructive inspection techniques for aero-engine blades, including conventional and computer vision-based approaches. Aust et al. [45] evaluated the accuracy of borescope and piece-part inspections of aircraft engine blades and assessed the detectability of different defect types under various conditions. The research sample included 50 participants, and the study analyzed the impact of various factors, such as blade perspectives, background color, and defect severities, on inspection performance. The study found that borescope inspection is more challenging than piece-part inspection and quantified the performance of human operators during inspections. Eye tracking was used to understand the visual search process, different search strategies, and inspection errors made by operators during inspections.

III. RESEARCH METHODOLOGY

This paper adopts a systematic literature review (SLR) research approach. This process entailed conducting an analytical review of recently published works on aero-engine blade defect detection. This process aimed to have a broad overview of the current technologies and methodologies used in aero-blade defect detection. SLR is a scientifically valid research methodology widely used to provide a high-level understanding of a given issue or phenomena based on already undertaken research [46], [47], [48]. SLR is considered particularly appropriate for generating insights from synthesizing previous research, especially as it concerns identifying emerging trends and research gaps [49].

This paper adopted the generic 3-stage approach to literature review as outlined by several previous studies [47], [48], [50], [51]. The first stage involved planning the literature review, which included identifying the scope of the review and relevant keywords for the literature search. The second stage involved executing the literature search process, which entailed searching for various publications through the Scopus search engine and downloading articles after reviewing their abstracts for relevance. The third stage consisted of reading through the articles with a focus on the specific objectives of this review and reporting the findings. As the introductory section notes, deep learning is critical in defect detection. Numerous deep-learning models have been developed for defect detection. This review identifies explicitly how these models are adapted for aero-blade defect detection. Therefore, articles on deep learning and aero-engine blade defect detection were sought. To execute the literature search process, we used the Scopus search engine, one of the largest databases of peer-reviewed literature. The search strings used for the review were designed to capture a broad range of articles on aero-engine blade inspection and defect detection. The search strings targeted relevant terms such as aero-engine, aircraft, blade, defect, damage, inspection, detection, and localization. The following search strings are used to search for articles on Scopus:

- (aero-engine OR aircraft* OR airplane*) AND (blade*) AND (defect* OR damage*) AND (inspection OR detection OR localization)
- (borescope OR videoscope) AND (jet-engine OR aero engine OR aircraft* OR airplane*) AND inspection

The selection of appropriate inclusion and exclusion criteria is critical to the quality of a systematic literature review. Table 3 shows this review's inclusion and exclusion criteria.

TABLE 3. Inclusion and exclusion criteria.

Inclusion	Exclusion
• Surveys and systematic literature reviews. • Publications from conferences, journals, magazines, and proceedings. • Methods that use deep learning techniques for aero engine blade inspection. • Papers published after 2015.	• The main language of the work is not English. • Non-deep-learning based inspection systems.

A. QUALITY ASSESSMENT

Quality assessment is a critical step in any systematic literature review. The quality assessment process aims to ensure that the articles included in the review meet a certain standard of relevance, rigor, and quality. To assess the quality of the articles for this review, several criteria were used, as illustrated in Table 4, including the relevance of the article topic to the research questions, the clarity of the objectives, the definition of the methods used, the adequacy of the literature review, and the relevance of the article's contribution to the research area. The first criterion examined whether the article topic was related to the research questions. This criterion ensured that the articles selected were directly related to the topic of deep-learning-based defect detection models for aero-engine blade inspection. The second criterion evaluated the clarity of the objectives of the article. This criterion ensured that the objectives were well-defined, specific, and measurable, providing a clear focus for the research.

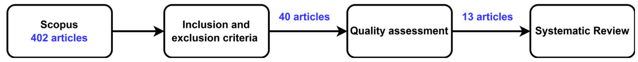

FIGURE 2. Literature search methodology.

The third criterion examined whether the methods used in the article were clearly defined. This criterion ensured that the methods used were rigorous, appropriate, and clearly described, enabling other researchers to replicate the study if necessary. The fourth criterion evaluated the adequacy of the literature review provided by the article. This criterion ensured that the article provided a thorough and up-to-date review of the relevant literature, demonstrating the author's knowledge of the research area.

The final criterion evaluated the relevance of the article's contribution to the research area. This criterion ensured that the article made a relevant and significant contribution to deep-learning-based defect detection models for aero-engine blade inspection, either by addressing an important research gap or proposing a new and innovative approach.

TABLE 4. Quality assessment.

No.	Question
Q1	Is the article topic related to the research questions?
Q2	Are the objectives clearly defined?
Q3	Are the methods clearly defined?
Q4	Does the article provide an adequate literature review?
Q5	Does the article contribute relevantly to the research area?

B. REVIEW EXECUTION

The search was limited to articles published after 2015. Given the rapid evolution of associated technologies, ensuring recency is essential to developing a useful systematic review for scholars and practitioners. Figure 2 details the framework used to select relevant articles. 402 search results are obtained after using the aforementioned search strings. Then, applying the inclusion and exclusion criteria, 40 articles are left for further screening. Applying the quality assessment measures listed in Table 4, 13 articles are identified as eligible for qualitative analysis. Table 5 shows the evaluation results of the selected articles.

TABLE 5. Evaluation of the selected articles.

Article	Q1	Q2	Q3	Q4	Q5
[52]	✓	✓	✓	x	✓
[53]	✓	✓	✓	x	✓
[54]	✓	✓	✓	x	✓
[3]	✓	✓	✓	✓	✓
[55]	✓	✓	✓	x	✓
[56]	✓	✓	✓	✓	✓
[57]	✓	✓	✓	x	✓
[58]	✓	✓	✓	x	✓
[32]	✓	✓	✓	✓	✓
[59]	✓	✓	✓	x	✓
[60]	✓	✓	x	x	✓
[61]	✓	✓	✓	x	✓
[62]	✓	✓	✓	x	✓

IV. RESULTS AND DISCUSSION

A. DESCRIPTIVE STATISTICS

A total of 13 studies were identified that specifically focused on defect detection in aero-engine blades. Although the number of included papers is small, most articles have been published over the last two years, as depicted in Figure 3. This indicates that there is growing research interest in this area.

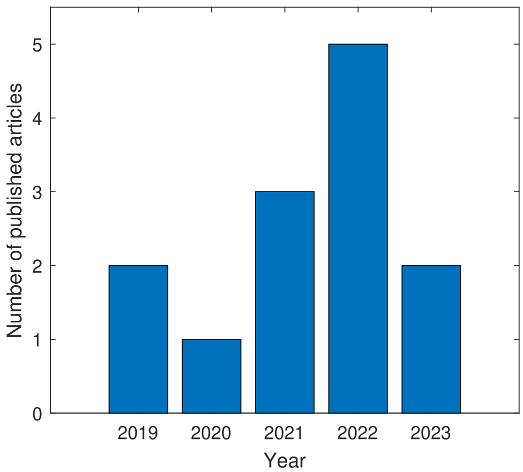

FIGURE 3. Number of published articles per year.

B. ADAPTED DEEP LEARNING MODELS

Kim and Lee [52] enhanced the CNN model through the addition of feature points extraction and matching. At the pre-processing stage, suspected damaged areas are selected from the videoscope. Comparative analysis of the videoscope image and the eigen-damage obtained through principal component analysis is undertaken. This is followed by the extraction of feature points from both images. Scale-invariant feature transform (SIFT) is used in the extraction of feature points with Random sample consensus (RANSAC) and K-dimensional (KD) used in the matching of feature points.

Then a CNN with two convolutional layers and two fully connected layers is deployed as seen in Figure 4 to classify the suspected damaged regions as defective or normal. The resulting classification of damaged and intact blades are shown in Figure 5. A total of 380 images were used for training, while 40 were used for testing the model, achieving a classification accuracy of 95.2%.

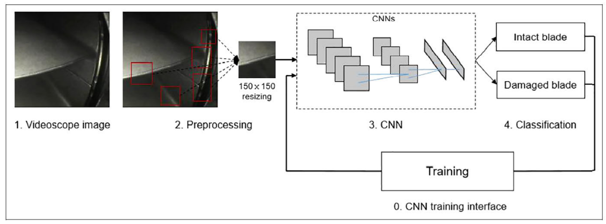

FIGURE 4. Two layer CNN model -damage recognition algorithm [52].

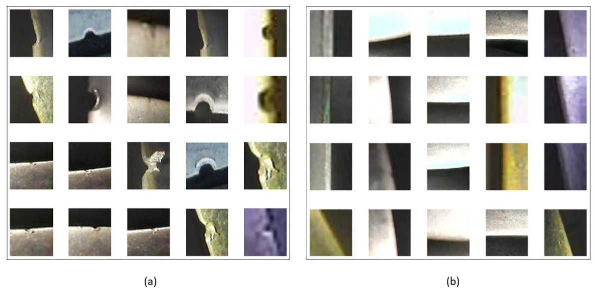

FIGURE 5. Classification results (a) damaged blade edges (b) intact blade edges [52].

Shen et al. [53] proposed a CNN-based framework for identifying and locating damages from borescope images. The framework is trained on borescope images to classify and locate two types of damage: crack and burn. The overall architecture is shown in Figure 6. The model architecture consists of six blocks: 5 convolutional blocks for feature extraction and 1 transposed convolutional block for damaged region recovery. A dataset of 1,443 images from three types of engines was collected, and 1,153 of these images were randomly selected into the training set. In contrast, the remaining images were left as the testing set. The proposed model was tested using a set of metrics and was compared with the human-labeled ground truth. The evaluation scores showed that the model scored 0.9803 for the Pixel Accuracy (PA) metric, 0.9726 for the Mean Accuracy (mA) metric, and 0.6789 for the Mean Intersect over Union (mIoU) metric. The detection results of the proposed method can be seen in Figure 7, which shows the successful detection of crack and burn defects.

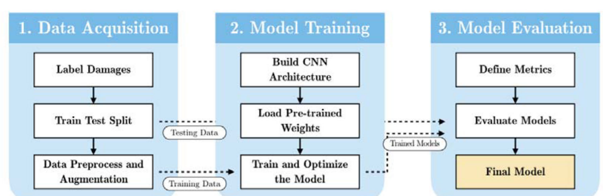

FIGURE 6. The overall architecture of the proposed framework [53].

Chen et al. [54] proposed the development of a fast and accurate feature weighting network (FWNet) based on

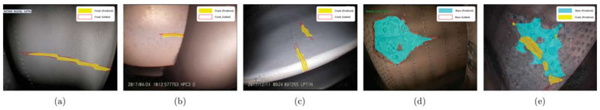

FIGURE 7. **Detection results. (a) The highlighted damage region, represented by yellow and cyan colors, for cracks and burns, respectively. Additionally, the human-labeled damage regions are marked with solid red lines. The proposed method can detect damages, including cracks and burns, regardless of their position, shape, size, and direction. (b) demonstrates the method's ability to distinguish between small cracks and blade gaps. (c) shows that the method can differentiate multiple cracks. Finally, (e) displays the successful extraction of the crack region from the surrounding burn region [53].**

the widely used CNNs and feature pyramids. The proposed model is shown in Figure 8. It incorporates a feature weighting module for channel-wise attention recalibration and enhancement of valid features' weights. The model utilizes a CNN for hierarchical extraction of defects with a feature weighting module (FWM) being used to recalibrate feature maps leading to enhanced feature propagation. Feature pyramid is constructed on top of ResNet architecture. Task-specific subnets are used to identify defects at varied scales. The model is evaluated on a dataset of 1,916 images with three categories of defects, achieving an mAP of 89.4%. Figure 9 shows the results of using this proposed model.

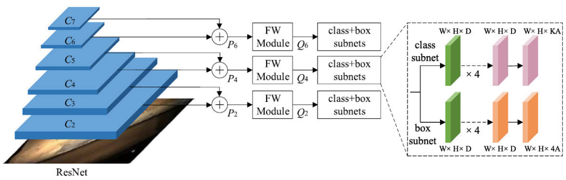

FIGURE 8. **Overall framework of the proposed method, where FW module denotes feature weighting module [54].**

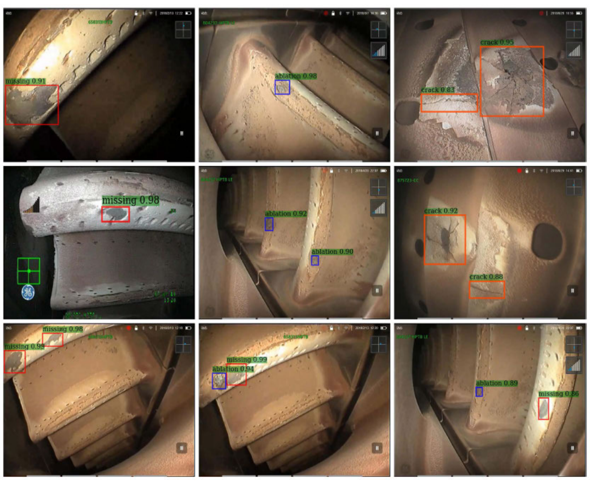

FIGURE 9. **Qualitative results of the proposed method using ResNet-101 and FWM [54].**

Li et al. [3] proposed a vision-based, coarse-to-fine defect detection system for aero-engine blades. High-resolution blade images are first cropped into smaller patches and passed to a convolution neural network (CNN) for feature learning. The CNN uses convolutional kernels of varying sizes and few pooling operations to identify defects in different scales. The coarse classifier is then used to exclude most non-defective patches; the remaining defective patches are forwarded to the fine detection module to classify and locate the defects. Their proposed model can be seen in Figure 10. The framework was trained and tested on a dataset of 24,848 images, achieving an accuracy of 93.5%, precision of 94.8%, recall of 96.1%, and F1 score of 95.4% for defect detection on aero-engine blade surfaces. Figure 11 shows the results of using this proposed model.

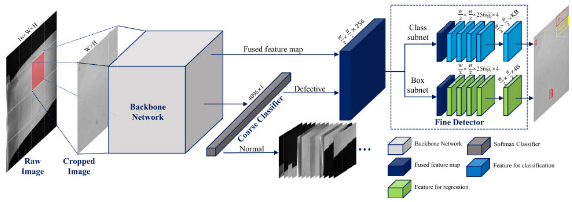

FIGURE 10. **The structure of the framework used to identify defects on aero-engine blade surfaces in large images. The framework consists of three modules: the backbone (feature extraction) network module, the coarse classifier module, and the fine detector module. The backbone network module learns to create high-quality feature maps, while the coarse classifier module filters out background images. The object fine detector module locates and accurately classifies defects [3].**

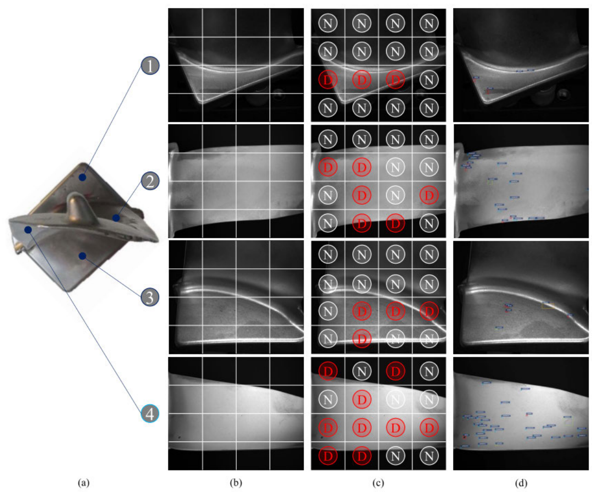

FIGURE 11. **Example of model results. (a) shows the aero-engine blade, with four regions marked for inspection. In (b), these regions are separated from the original raw image. The coarse classified results for defect detection are shown in (c), with "N" representing regions classified as normal and "D" representing regions classified as defective. Finally, in (d), the defect localization and fine classification results are shown for each of the four regions on the aero-engine blade surface [3].**

Wong et al. [55] introduced a system for automatically detecting and assessing damage on gas turbine blades. The system employs a mask R-CNN network model as in Figure 12 capable of segmenting defective regions within the frames obtained from a borescope. A dataset of 104 manually annotated images covering five defect classes is used to train and evaluate the model. Some of the results from this study are shown in Figure 13. The mAP for the model was 0.82, and the intersection over union (IoU) was close to 0.87.

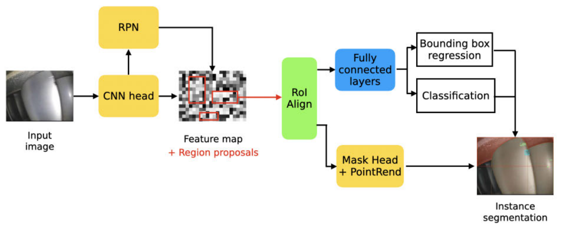

FIGURE 12. Simplified schematic of the Mask R-CNN [55].

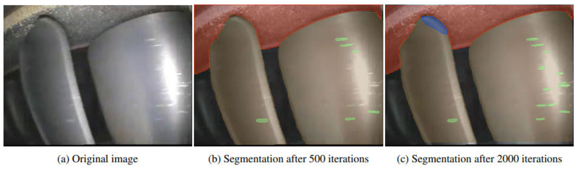

FIGURE 13. Segmentation results for a frame showing rotors 46 and 47 after 500 and 2000 training iterations. Note that this frame is not in the training data [55].

Jaeger et al. [56] proposed a ResNet-18 CNN model to identify turbine blade images as crack or crack-free. An infrared camera and pulsed induction thermography are used for collecting the dataset. Two approaches are used for training; training the model on the original dataset and training on randomly cropped image patches with a resolution of 64 × 64. The latter approach achieved better performance with a precision of 63% and a recall of 93%.

Li et al. [57] enhanced the YOLOv5 model by introducing a K-Means Clustering Algorithm, ECA-Net mechanism, and BiFPN module. K-means Clustering replaces the default anchors in the YOLOv5 model to enhance the extent of matching across anchors and object frames. Figure 14 shows the architecture of the model. According to Li et al. [57], the main rationale behind the creation of the K-Means Clustering algorithm is to ensure random selection of the k clustering centers at the outset of the process, distribution of samples for classification and recalculation of the mean value of objects in order to create a new cluster center. ECA-Net is incorporated into the backbone network to optimize efficiency across channels and emphasize the extraction of features from defect areas. BiFPN module adapted from the EfficientDet network is used to replace the PANet present in the YOLOv5 network to ensure full integration of features at varied scales and enhancement of accuracy. A dataset of 3,500 images with four defects is used to train and evaluate the model, which achieved an mAP of 98.3%. Figure 15 Compares the detection results of two models, the original YOLOv5s model, and the YOLOv5s KEB model.

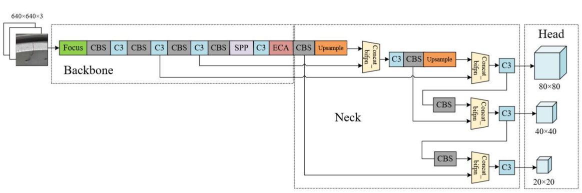

FIGURE 14. The architecture of the YOLOv5s-KEB model [57].

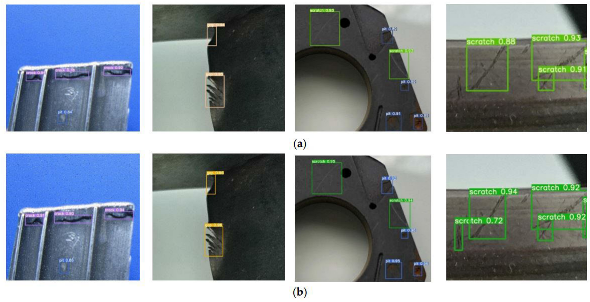

FIGURE 15. Comparison of detection results of (a) YOLOv5s model and (b) YOLOv5s KEB model [58].

Li et al. [58] adaptation of the YOLOv5s model entailed the addition of deformable convolution and depth-wise separable convolution. The addition of deformable convolution (DConv) is to enhance CNN's ability to model deformed objects and better extract object features from the image. At the same time, it also enhances the YOLOv5s network's ability to overcome challenges with CNN's poor geometric transformability and to improve the capacity for adaptation of feature maps with highly varied shapes. The incorporation of depth-wise separable convolution (DSConv) is to undertake double extraction of features across two layers. The first layer extracts feature, with the second layer integrating features from varied channels. This serves to reduce the computational power required and also limits the size of the trained model needed. A dataset of 850 borescope images from airliner aircraft containing 5 different categories of defects is used. The model attained a precision of 93.3%, recall of 76.2%, and mAP@0.5 of 81.9 %.

Shang et al [32] introduced a global prior Transformer network (GPTNet) into the borescope inspection method as shown in Figure 16. Their proposed novel GPTNet utilizes a local window Transformer network (LWTNet) for image feature extraction and a global label graph network (GLGNet) for extraction of label features. Both are used in locating and classifying image features. A dual graph convolutional network (GCN) is also adopted for multi-label image classification. Overall, the transformer network models pixels across each layer of the transformer thus providing clarity on defects contours with very limited loss of information. Three datasets are used to evaluate the model: the Aluminum dataset, a dataset of simulated blades, and a dataset of real blades The simulated blade dataset consist of 3,000 images with five defect categories, whereas the real blade dataset contains 131 borescope images. The model showed an mAP @0.5 of 84.9% on the simulated blade dataset and an mAP @0.5 of 54.4% on the real blade dataset.

Shang et al. [59] enhanced Mask R-CNN by introducing texture-focus multi-scale feature fusion network (TFNet), balanced L1 (BL), and Multi-type damage evaluation metric, as depicted in Figure 17. TFNet delivers greater detail of shallow texture, which better reflects the defect types. BL is added to balance coarse and fine-grained locales through adjustment of gradient and loss. BL is also used for

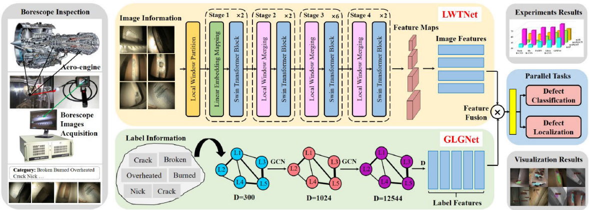

FIGURE 16. GPTNet diagram [32].

segmentation, localization, and classification. For the backbone, a feature pyramid is utilized. The model is evaluated on two datasets: the simulated and real blade datasets. 3D printing and laser machining are used to produce the simulated blade dataset leading to 3,000 images with five damage categories. The real dataset consists of 524 borescope images. On the simulated blade dataset, the model attained an mAP of 60.4% for bounding box localization and 55.1% for segmentation. The model evaluated on the real blade dataset (using a ResNet-101 backbone) achieved 62.4% mAP for bounding box localization and 61.2% mAP for segmentation.

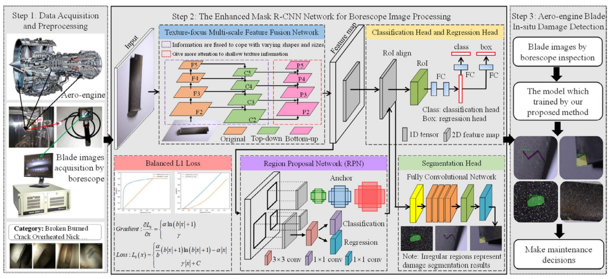

FIGURE 17. Enhanced Mask R-CNN detection model [59].

Jiao et al. [60] developed a novel ensemble learning model that combines base classifiers to create an even stronger classifier. Adaptive boosting and bootstrap aggregation ensemble models are utilized in the synthesis of outputs from multiple classifiers. The proposed model identifies defects based on ultrasonic signal-extracted features. The amplitude of echo signals varies based on defect sizes. Continuous wavelet transform (CWT) is used to obtain the time-frequency function. The resulting dataset of 2,500 sequences covers three defect categories. Adaptive boosting achieved an average F1 score of 0.77, while bootstrap aggregation achieved an average F1 score of 0.85.

Wang et al. [61] introduced the DBFF-YOLOv4 method for classifying and localizing defects in aero-engine turbine blades. The model deploys two CNN backbones for feature extraction, namely CSPDarknet53, and ResNet-50. The path aggregation and feature pyramid networks are used for fusing features. A dataset of 2,137 X-ray images with a resolution of 770×1700 is obtained by cropping the raw x-ray films. The dataset covers six internal defect classes. The model achieved a 96.7% precision and 91.87% recall.

Using the generative adversarial network (GAN) model shown in Figure 18, Wang et al. [62] proposed a system for detecting defects in X-ray images of turbine blades. The model is trained using non-defective X-ray images by minimizing the distance between the encoding vectors of the generated image and the original. Then, defect detection is achieved using a GAN that reconstructs non-defective samples but not those with defects. The model achieved a detection accuracy of 0.911 using 2,000 X-ray images of turbine blades with an input image size of 128×128 and 600 encoding size.

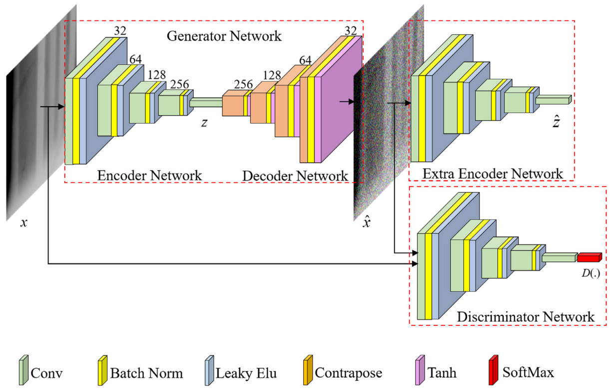

FIGURE 18. GAN damage classification model [62].

Overall, 13 studies that adopt deep learning models for aero engine blade inspection are analyzed. Tables 6 and 7 summarize the main findings of these studies.

C. REMARKS ON THE ADAPTED DEEP LEARNING MODELS

This section covers the advantages and complications of using the previously discussed deep learning models in section IV-B.

The reviewed deep learning models for aero-engine blade defect detection showcase a variety of innovative and effective techniques for defect detection, including CNNs, FWNets, ensemble learning, YOLOv5, GPTNet, and mask R-CNNs, among others. Many of these models use a combination of classification and localization to detect multiple types of defects. Some employ feature pyramid networks or other techniques to improve the detection of defects at different scales or resolutions. Additionally, several models use modified versions of existing models to improve their speed and accuracy. For example, YOLOv5s and DBFF-YOLOv4 use backpropagation feature fusion and deformable convolution to enhance their detection accuracy. GPTNet uses a local window Transformer network (LWTNet) and a global label graph network (GLGNet) to extract image features and classify defects. These models demonstrate the power of deep learning for detecting and classifying defects in complex industrial settings.

However, these models also present some limitations. The models in [32] and [59] have relatively low accuracy or mAP metrics, which may limit their practical usefulness. The quality and size of the datasets used to evaluate these models vary significantly, making comparing their performance challenging. Additionally, some models, such as [3], [32], and [52], and [57], use complex architectures and extensive

TABLE 6. Adapted deep learning models for aero-engine blade defect detection.

Year	Paper	Model	Features	Dataset	Accuracy	F1 score	mAP	IoU
2019	[52]	CNN	• Binary classification: Normal and abnormal. • SIFT is used to extract feature points. • Random sample consensus and K-dimensional are used for matching feature points. • a CNN with two layers is deployed for damage classification.	420 borescope images	95.2%	-	-	-
2019	[53]	CNN	• Multiclass classification: crack and burn. • Five convolutional blocks for feature extraction and one transposed convolutional block for damaged region recovery.	1443 images	97.26%	-	-	67.9%
2020	[54]	FWNet	• Multiclass classification: missing coating, crack, and ablation. • Bounding box localization. • Feature weighting module for channel-wise attention recalibration. • A feature pyramid on top of ResNet architecture.	1916 borescope images with three categories of defects	-	-	89.4%	-
2021	[60]	Ensemble learning	• Multiclass classification: Inclusion, cavity, and crack. • Adaptive boosting and bootstrap aggregation ensemble models are utilized in the synthesis of outputs from multiple classifiers.	2500 ultrasonic sequences	-	85%	-	-
2021	[3]	Coarse-to-fine	• Multiclass classification: scratch, pockmark, fold, pit, and strain. • Bounding box localization. • A coarse classification module to filter out non-defective regions. • A fine detection module to classify and locate the defects.	24,848 images with five defect categories	93.5%	94.7%	-	-
2021	[55]	Mask R-CNN	• Binary classification. • Defect instance segmentation.	104 annotated images with five defect categories	-	-	82%	87%
2022	[56]	CNN	• Binary classification: crack or crack-free. • A Resnet-18 backbone.	652 infrared images	-	75%	-	-

preprocessing operations that may be difficult to train or deploy. In contrast, others lack important implementation details that make them more reproducible. Finally, while many of these models can detect multiple types of defects, some are designed only for binary classification ([52], [55], [56], [62]) or for specific types of defects.

According to analyzed studies, several prominent trends have emerged.

- Deep learning models have demonstrated impressive levels of accuracy in identifying and localizing defects on aero engine blades, with some studies achieving accuracy rates surpassing 90%. Researchers have also found that utilizing multiple CNNs and ensembles of classifiers can further enhance the accuracy of defect detection.
- CNN models have become a popular choice for this application, with researchers incorporating enhancements such as deformable convolution, depth-wise separable convolution, and feature weighting modules to improve their efficacy.
- Most recent models focus on a multiclass classification to detect and classify multiple types of defects, such as scratches, cracks, pits, missing coatings, and ablations. This is crucial for practical applications since different defects require different maintenance approaches.
- Dataset size is a crucial factor in achieving high accuracy. The studies with larger datasets tend to achieve higher accuracy than those with smaller datasets.
- The dominant learning approach is supervised learning, with only one study employing an unsupervised learning approach (GAN).

To this end, these findings have significant implications for researchers and practitioners alike in the field of aero-engine blade inspection, emphasizing the importance of utilizing advanced CNN models and large datasets to improve defect detection accuracy.

TABLE 7. Adapted deep learning models for aero-engine blade defect detection (continued).

Year	Paper	Model	Features	Dataset	Accuracy	F1 score	mAP	IoU
2022	[57]	YOLOv5	• Multiclass classification: scratch, crack, gap, and pit. • Bounding box localization. • Calculation of anchor parameters using K-Means Clustering. • ECA-Net incorporated into the backbone network to emphasize extraction of features from defect areas.	3500 images with four types of defects	-	-	98.3%	-
2022	[58]	YOLOv5s	• Multiclass classification: dent, crack, missing material, corrosion and TBC missing. • Bounding box defect localization. • Addition of deformable convolution and depth-wise separable convolution.	850 borescope images with five defect categories	-	83.8%	81.9% (@0.5)	-
2022	[32]	GPTNet	• Multiclass classification. • Bounding box defect localization. • A local window Transformer network (LWTNet) for image feature extraction. • A global label graph network (GLGNet) for extraction of label features. • A dual graph convolutional network (GCN) is also adopted for multi-label image classification.	• Aluminum dataset (3005 images) • simulated blades dataset (3000 images) • Real blades dataset (131 images)	-	-	54.4% (@0.5)	-
2022	[59]	Mask R-CNN	• Multiclass classification. • Bounding box localization and segmentation. • A texture-focus multi-scale feature fusion network (TFNet) is introduced to capture greater detail of shallow texture. • ResNet-101 backbone.	• A simulated blades dataset of 3000 images • A real blades dataset of 524 images	-	-	62.4%	-
2023	[61]	DBFF-YOLOv4	• Multiclass classification: remainder, broken core, slag inclusion, gas cavity, cold shut, and crack. • CSPDarknet53 and ResNet-50 are used for feature extraction. • Feature pyramid networks are used for fusing features.	2137 X-ray images	-	94.2%	-	-
2023	[62]	GAN	• Binary classification: defective and non-defective. • Non-defective X-ray images are used to train the model.	2000 X-ray images with five defect categories	91.1%	-	-	-

D. OBSERVED CHALLENGES

The reviewed studies provide promising progress in the automation and accurate detection of aero-engine blade defects, but these studies have also revealed several limitations. To overcome these challenges, researchers must focus on advancing the field of deep learning-based defect detection models for aero-engine blade inspection. The main challenges can be summarized as follows:

1) DATA IMBALANCE

The literature analyzed in this study indicates that data imbalance is a frequent challenge encountered when detecting aero-engine blade defects [3], [32], [52], [56], [58], [59], [63]. This occurs when normal samples greatly outnumber defective or training data fails to represent all defect categories equally. This can result in a model bias towards the over-represented classes, and performance metrics such as precision and recall might be deceptive in this case. For instance, a model that achieves high accuracy may still perform poorly in detecting the underrepresented classes of defects. Thus, it is essential to address data imbalance to ensure the model can accurately identify all defect categories.

2) DATA SCARCITY

Several of the reviewed studies were impacted by data scarcity and high annotation costs, which can affect the quality and size of the training dataset [3], [32], [52], [55]. Annotating sensory data or images can be time-consuming and labor-intensive, particularly for identifying aero-engine blade defects. This is because it requires annotations from multiple experienced personnel to avoid labeling errors. As a result, the annotation process can be expensive, making it difficult to obtain a sufficiently large and high-quality dataset.

3) SENSITIVITY TO NOISY DATA

The performance of defect detection algorithms can be significantly impacted by the quality of the data utilized for training and testing, particularly in regards to sensitivity to noisy data [32], [55], [62]. Certain detection models may erroneously identify noise as a defect, leading to an increase in the false positive rate and significant degradation of overall performance. Therefore, it is imperative to ensure the data's quality and implement robust preprocessing techniques to filter out the noise and minimize its impact on model performance.

4) LACK OF BENCHMARKS

The absence of a standardized benchmark dataset for evaluating the performance of defect detection models is also a significant challenge. All the reviewed papers use custom datasets that are not publicly available. A benchmark dataset is essential for comparing the performance of different models and monitoring the field's progress. So, there is a need to collaborate between industry and academia to create publicly available benchmark datasets and standardized evaluation metrics for aero-engine blade defect detection, enabling fair comparison of different models and facilitating the development of more effective algorithms.

5) NOVEL DEFECTS DISCOVERY

The main challenge of the reviewed studies is the inability to detect new or emerging classes of defects that were not included in the training dataset. Deep learning models have shown great potential in detecting blade defects and improving the accuracy and efficiency of visual inspection. However, these models rely heavily on training data to identify and classify defects accurately. In cases where new or emerging defects that are not part of the training data arise, these models might fail to detect such defects.

V. CONCLUSION

In conclusion, the reviewed studies indicate that deep learning models have the potential to enhance the accuracy and efficiency of detecting aero-engine blade defects. CNN and YOLO are the most popular generic deep-learning models being adapted for this specific application. However, several challenges, such as data imbalance, data scarcity, sensitivity to noisy data, lack of benchmarks, and inability to detect new or emerging defects, need to be addressed for the practical application of these models. These findings suggest that the technology is still in its early stages of development, resulting in a low Technology Readiness Level (TRL). Therefore, future research should address these issues and improve the overall quality of aero-engine blade inspections based on computer vision to advance the field toward a more automated and effective defect detection system in the aerospace industry.

A. FUTURE RESEARCH DIRECTIONS

It is recommended that future research in this field should consider exploring the potential of unsupervised and self-supervised learning models. These models have shown promise in various applications, including image classification, object detection, and anomaly detection [64]. They offer several advantages, such as reducing the need for extensive labeled data and enabling the detection of novel defects. Thus, incorporating unsupervised and self-supervised learning models into the repertoire of techniques employed in aero engine blade inspection may improve accuracy and efficiency, ultimately benefiting the aviation industry.

In light of the challenges of obtaining a sufficient volume of defect data for developing deep learning models for aero engine blade inspection, the real-time acquisition of defect data and model training during the inspection process could address this issue. This approach acknowledges the time-sensitive nature of inspection tasks and that most defective blades are repaired and returned to service. Stationing a deep learning model at the source of inspection could provide access to the necessary data for effective training, subsequently improving the model's robustness and performance.

Another promising direction for future research involves incorporating multi-modal data, such as combining visible-light images with infrared or ultrasonic data, to improve the defect detection capabilities of the models. This approach can enhance accuracy by providing additional information about defects not apparent in traditional visible-light images.

Furthermore, researchers should investigate the potential of active learning approaches in aero-engine blade inspection. Active learning refines the model by iteratively selecting and annotating the most informative samples, leading to more efficient use of available labeled data. This approach can also help develop models that adapt to changing defect characteristics over time.

ACKNOWLEDGMENT

The authors would like to thank ARIC and Sanad for their continuous support of research.

(Yusra Abdulrahman and M. A. Mohammed Eltoum contributed equally to this work.)

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