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Smart Defect Detection in Aero-Engines: Evaluating Transfer Learning with VGG19 and Data-Efficient Image Transformer Models

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Abstract: This study explores the impact of transfer learning on enhancing deep learning models for detecting defects in aero-engine components. We focused on metrics such as accuracy, precision, recall, and loss to compare the performance of models VGG19 and DeiT (data-efficient image transformer). RandomSearchCV was used for hyperparameter optimization, and we selectively froze some layers during training to help better tailor the models to our dataset. We conclude that the difference in performance across all metrics can be attributed to the adoption of the transformer-based architecture by the DeiT model as it does this well in capturing complex patterns in data. This research demonstrates that transformer models hold promise for improving the accuracy and efficiency of defect detection within the aerospace industry, which will, in turn, contribute to cleaner and more sustainable aviation activities.

Keywords: transfer learning; defect detection; aero-engine components; transformer models; deep learning

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1. Introduction

Defects in aero-engine parts affect security, increase the danger of energy inefficiency, and endanger the ecosystem. For safety reasons, details like gaps or other structural fractures might be stress raisers, which may affect the reliability of the parent engine, resulting in a higher probability of extreme failure or repair that was not planned [1]. Moreover, these faults can also reduce aerodynamic and thermal efficiency and, therefore, increase the work requirements to maintain thrust levels of the engine and hence its fuel use [2,3]. Cracks, which are minor details, can increase fuel requirements, which can then lead to increased emissions [4]. Therefore, to maintain operational safety and operational cost through fuel economy, replacing or mending broken parts should be performed expeditiously in the aerospace industry. IoT devices for automated defect detection can minimize these inefficiencies not only in fuel economy but also in operational cost [5,6]. ICAO, in one of its reports, noted that advanced detection of fuel fraud systems can stop millions of metric tons of fuel from being burned by processes other than the combustion of greenhouse gases [6]. Furthermore, degradation in key aero-engine components can result in additional fuel consumption, emphasizing the importance of early detection. Techniques like Engine Health Monitoring (EHM) can significantly reduce inefficiencies and extend component lifespan by identifying defects before they lead to severe performance issues [7].

Defects in aero-engine components lead to increased fuel consumption and environmental impact. Studies show that engine deterioration can cause up to a 4.5% increase in fuel consumption over the engine's lifecycle [8]. This results in higher operational costs and adds to carbon emissions. By employing predictive maintenance techniques such as Engine Health Monitoring (EHM), airlines can reduce inefficiencies, saving fuel and lowering emissions [7]. For instance, when engines operate under degraded conditions, their fuel efficiency drops, which can cause a significant rise in exhaust gas temperatures. Incorporating advanced diagnostic tools can prevent such inefficiencies, allowing for timely maintenance interventions that minimize energy loss and extend component life [9]. The presence of cracks and surface imperfections on components like turbines and compressor blades in aero-engines is a significant concern since such defects limit the aircraft engines' performance and reliability. These blades are subject to extreme temperatures and pressures, but even the slightest structural defects make these blades vulnerable to several mechanical failures [10]. For instance, if any small crack appears, it changes the flow dynamics throughout the blade, which, in turn, causes imbalance and increased drag areas, thus altering overall engine efficacy. Such disruptions make the engine work harder to provide the same thrust, forcing the engine to burn through more fuel, which ultimately raises both operational costs and the carbon footprint [11]. If not compensated, such a defect can be quite detrimental as it shifts the blade angles, directly affecting their hydrodynamic performance as air cannot drown smoothly around the blade's surface. Over time, this changed angle increases fuel usage and, ultimately, more greenhouse gas emissions. Furthermore, cracks also lead to localized high stresses, which further damage the engine parts and result in lower service lives for the components and even less economical maintenance [12]. Nondestructive inspection techniques like eddy current testing, ultrasonic testing, and radiography have traditionally been used to detect these defects in aero-engine blades [13].

Nevertheless, these techniques remain dependent on highly competent inspectors and may overlook small surface irregularities, which result in the inability to comprehend a given defect in its entirety [14]. The reliance on deep learning-based AI algorithms in automating the detection process has increased the likelihood of obtaining even the most minor cracks with more excellent repeatability while decreasing the amount of human error present [15]. Predictive maintenance techniques can significantly augment industrial systems by enabling intelligent, multi-omics approaches that include decision making during real-time control. Such strategies are particularly suitable for the problems and objectives in the field of aero-engine maintenance and repair within the fracture zone and above [16]. Furthermore, experimental analyses of TA-48 multi-stage centrifugal compressors enrich the understanding of fault diagnosis and prediction methodologies in the manufacturing domain, thereby validating the role of machine learning algorithms in the reliability and efficiency of the system [17]. In addition, the advanced technologies of Industry 4.0 have also made smart inspections emerge in industries, including wind energy production [18,19]. For example, smart inspection frameworks for wind turbine blades are crucial in ensuring the sustainability and efficiency of these devices, thus further demonstrating the need for smart inspection strategies in damage assessment and planning of general maintenance. In addition, non-contact inspection techniques, including thermography, laser stereography, and machine vision, are quickly becoming important tools for inspecting wind turbine blade defects, considering techno-economic issues and the concept of the Fourth Industrial Revolution [20]. The robustness of fixtureless inspection methods for nonrigid parts has been validated using a Kolmogorov–Smirnov (K–S) test to compare Computer-Aided Inspection (CAI) results with actual measurement of defects. By integrating the finite element nonrigid registration (FENR) technique and compensating for synthetic noise effects, these techniques accurately measure defect amplitude, area, and distance distributions, even under noisy conditions [21]. The efficiency of utilizing CAI in smart inspection systems is the minimization of human efforts in system usage. Integrating CAI leveraging Industry 4.0 tools enables automated quality control with less human effort. This methodology aligns with a comprehensive intelligent framework for defect detection and real-time monitoring, as discussed in the smart inspection and sustainability model [22]. Some of the attributes of Maintenance 4.0 modernization include the incorporation of digital twins, continuous monitoring, and predictive maintenance. Large and small- to medium-scale industries implementing these approaches enable green manufacturing practices as these processes should be of utmost concern for industries promoting an eco-friendly economy [23]. By eliminating the need for physical fixtures, automatic virtual inspection methods for nonrigid parts deliver accurate defect detection by effectively separating true geometric deviations from flexible deformations. Leveraging advanced filtering techniques such as curvature and von Mises stress, these methods increase accuracy while reducing reliance on costly fixtures, as demonstrated in aerospace applications [24]. Smart geometric nondestructive evaluation methods mark a major step forward in incorporating AI and Industry 4.0 technologies into inspection systems. They enhance efficiency, boost detection rates, and improve the interpretability of inspection processes. In contrast to traditional approaches, these innovations enable virtual inspection systems to adopt automated smart inspections, as highlighted in recent research [25]. Integrating automated detection can significantly improve gas turbine engine efficiency. Deep learning-based approaches now target microscopic defects in aero-engine blades, using models like convolutional neural networks (CNNs) and enhanced YOLO variants. These architectures achieve high-accuracy, real-time defect classification, substantially cutting down on manual inspections. A systematic review shows that these frameworks improve detection accuracy and streamline the entire maintenance process, reducing fuel consumption and emissions [26]. Furthermore, the review addresses the exploitation of advanced deep learning approaches. Moreover, the review explores advanced deep learning techniques, such as Global Prior Transformer Networks (GPT-Net) for aero-engine maintenance. This model offers enhanced capabilities in detecting and classifying defects, enabling more proactive maintenance strategies to prevent system failures. Such deep network applications align with sustainability objectives by minimizing fuel usage and lowering the aerospace sector's cost [27].

Deep learning improves defect inspection and quality control by automating processes and increasing accuracy. Traditional methods use handcrafted features, which may not always represent the large diversity of defects well. In contrast, deep learning architectures may be more robust and discerning because they are trained to take these characteristics straight from the data. Systems that use convolutional neural networks (CNNs) for defect detection offer substantial advantages over other approaches, largely due to their strong performance in image processing. One standout example is VGG19, introduced by Simonyan et al., which is recognized for its deep architecture and small receptive fields, enabling detailed feature extraction. VGG19 has also found applications in defect detection across several industries [28]. Wan et al. [29] thus used a form of transfer learning based on the VGG19 model to learn to detect defects in the surface of strip steel. The study faced the detection of numerous and complicated surface defects in the strip steels, which the conventional pictures could not effectively solve as they are less efficient in recognition and generalization. By freezing the appropriate pre-trained layers in VGG19 and modifying their learning rate to fit the use of the model, the group obtained a recognition rate of 97.5% on the NEU surface dataset. This method showed considerable improvement over other types of machine learning techniques. It proved the potential of using deep learning and transfer learning for defect detection when the number of samples or the image quality is low. In a recent study, Thakkallapally [30] introduced a VGG19-based CNN model for classifying weld defects in radiography images. The model was trained on a dataset of 3000 images (128 $\times$ 128 pixels), divided into three categories. By leveraging transfer learning on a Tesla K80 GPU, the model achieved a training accuracy of 93.17%, a validation accuracy of 91.14%, and a test accuracy of 91%. This approach highlights the potential of deep learning to streamline inspection processes and reliably detect weld defects in industrial environments. Another study carried out by Alptekin Durmuşoğlu et al. [31] investigated the identification of fabric defects using convolutional neural networks during an IEEE Conference. It was observed in their study that fabric defects result in a reduction in the quality of the product, and this is often controlled by visual inspection, which is quite faulty, with errors as high as 40%. To address this, the authors implemented the convolutional neural network classifier VGG19 model to automatically classify fabric defects. Their findings revealed that the application of the VGG19 model could detect fabric defects, indicating that this model can efficiently automate the fabric quality assurance process, thereby reducing manual interventions and improving the performance of the processes in the textile sector.

Transformer-based approaches were originally designed for natural language processing, but transformers have recently been adapted to computer vision tasks, yielding promising outcomes [32]. The papers of Dosovitskiy et al. [33] provide evidence of a paradigm shift in the processing of image data, where instead of treating images as single states, they began to be treated as sequences of image patches, with self-attention mechanisms being employed to extract intricate structures within the data. In addition, Touvron et al. [34] suggested the DeiT model, whose purpose is primarily efficiency and achieving performance even when smaller datasets impact scalability. Evidence of some safety nets within these practices can be found in a greater number of effective long-range dependencies and greater contexts within images, as became evident when transformers were being used to detect defects [35]. In their research, Xie et al. [36] presented yet another model. In this case, DPiT was intended for defect detection of photovoltaic solar cells using a transformer-based approach. The model significantly outperformed others when tested against common methods, including CNN-based approaches, achieving a first-rate accuracy level of 91.7% in the Elpv dataset, which reinforces the case for the applicability of transformers in this niche. Likewise, An et al. [37] noted improved performance in detecting manufacturing defects of printed circuit boards when using the transformer model, which enhances the strong edge of traditional models in terms of small and complex defects. Wang et al. [38] conducted a comparison between hybrid transformers and CNN in detecting geological faults. They discovered that although CNN-based models, especially those combining CNNs and ViTs, are proficient in feature extraction, pure ViT models demonstrate greater noise tolerance and data efficiency. ViT models, particularly those pre-trained on ImageNet, offer precise fault predictions with minimal training data, underscoring their potential to enhance seismic fault detection [39]. In a recent study, Sarmadi et al. [40] explored how vision transformer (ViT) models can be used to diagnose osteoporosis by analyzing X-ray images. They compared the performance of these ViT models with more traditional CNNs and discovered that the ViTs outperformed their CNN counterparts. This finding points to the significant potential of vision transformers in medical image analysis.

The aerospace sector imposes rigorous requirements on the inspection and upkeep of essential components like aero-engines. Traditional manual inspections are increasingly complemented by automated techniques enabled by deep learning, which provide the potential for quicker, more precise, and more reliable defect detection. Shen et al.'s [41] aim was to provide a deep learning framework that would enable greater and faster damage detection to aircraft engines. The framework applies Fully Convolutional Networks (FCN) to identify and classify damaged parts using video images from a borescope, like cracks and burns. Everybody wins when the authors apply fine-tuning techniques; the necessary training measurement decreases, and the entire system becomes more efficient. This alien framework was tested on real-world data from an airline, and the results of damage detection performed by the framework defined it as more advanced than the classical solutions built on CNN architectures. Upadhyay et al. came up with a deep learning framework to detect defects in aircraft engines, which satisfied the precision and recall metrics above 90%. The model comprises customized U-Net and a GAN to enhance the images, but it has limitations in detecting extremely tiny defects. Abdulrahman et al. [42] prepared a survey on deep learning approaches used to detect defects in aero-engine blades. This research also mentions the promise of models like CNN and YOLO for increasing inspection effectiveness and some limitations, including the lack of data and sensitivity to noise. The present authors emphasize that future studies should target unsupervised learning, real-time processing of the incoming data, and multi-modal means to improve the quality of defect detection and system resiliency. Zubayer et al. [43] developed a deep learning approach using YOLOv8 to detect surface defects on the turbine and compressor blades of jet engines made using additive manufacturing. This method achieved 99.5% accuracy in only 280 s, representing a rapid and cost-effective quality control alternative for the aerospace industry. Zhang et al. [44] proposed a transformer-based approach for the detection of defects in turbine blades of aero-engines with advanced multi-scale fusion and attention to detail. This method is helpful for problems such as multi-scale defects and imbalanced datasets as it beats previous techniques and is beneficial for aerospace quality control. A new multi-headed attention network for intelligent borescope inspection of aero-engine blades has been proposed by Shang et al. [45]. Their Global Prior Transformer Network enhances surface damage identification by establishing pixel-to-pixel relationships and label information via a graph convolution network. The approach achieved an 84.9 mAP on a simulated blade dataset, demonstrating its effectiveness in practical applications. Table 1 outlines the core literature themes, covering the impact of cracks on fuel efficiency, traditional vs. automated NDI, predictive maintenance within Industry 4.0, deep learning methods, and advanced aero-engine detection [27].

Table 1. Overview of key literature themes and their relevant references.

Main Subject/Focus	References
Cracks and Fuel Efficiency Discusses how minor imperfections (e.g., cracks) in aero-engine components increase fuel consumption and emissions and emphasizes the need for early detection to mitigate performance losses.	[1–10,12]
Traditional vs. Automated NDI Compares conventional nondestructive inspection (NDI) techniques (eddy current, ultrasonic, and radiography) with automated or AI-based methods, highlighting the limitations of manual approaches.	[13–15,18,19,25–27,41–45]
Predictive Maintenance and Industry 4.0 Covers real-time monitoring, Industry 4.0 frameworks, fixtureless inspection methods, and smart inspection systems that reduce downtime, extend equipment life, and enhance sustainability.	[16–25]

Table 1. *Cont.*

Main Subject/Focus	References
Deep Learning Approaches (CNN and Transformers) Demonstrates the use of CNNs (e.g., VGG19) and transformer-based models (e.g., ViT, DeiT) for detecting micro-level defects in various domains, including aero-engine components.	[14,15,26–45]
Advanced Aero-Engine Defect Detection Focuses on specialized models (FCN, YOLO, and Global Prior Transformer) and case studies for high-accuracy defect detection and smart borescope inspections, showing how these methods improve reliability and reduce fuel consumption.	[26,27,41–45]

The recent literature confirms that AI-driven inspection is viable for Maintenance, Repair, and Overhaul (MRO) facilities and on-wing scenarios. Shang et al. proposed a Mask R-CNN-based pipeline that accurately localizes and segments blade damage in borescope images, while Uzun employed Faster R-CNN with an Inception v2 feature extractor to detect cracks, burns, dents, and nicks in actual borescope data with average accuracies above 88% [46]. A subsequent study by Shang et al. [47] introduced a graph neural network to handle irregular texture patterns better and enhance in situ detection reliability. Meanwhile, comparative analyses by Aust and Pons indicate that deep learning approaches can perform at least as consistently as human operators, mitigating issues like fatigue or subjectivity; Aust et al. [48,49] extended these insights with a decision support system for gas turbine blade inspections. Other works address specialized tasks, such as the automated detection of surface irregularities on additively manufactured blades [44], systematic risk assessments of visual inspection [50,51], and performance prognostics from an airline perspective. Studies by Ezhilarasu et al. [52] and Doğru et al. [53] highlight how CNN-based frameworks can integrate into broader aircraft maintenance workflows, while additional advances like knowledge transfer in aircraft design, long short-term memory networks for remaining useful life estimation, and sensor-based load monitoring point to a growing industrial focus on deep learning solutions [53–55]. Collectively, these deployments validate CNN- and transformer-based methods for practical, near real-time defect detection in aero-engine MRO environments, underscoring the industrial relevance of our proposed approach.

Recent advances in deep learning have yielded significant progress in the automated detection of aero-engine defects. For instance, Li et al. propose a coarse-to-fine framework tailored explicitly for high-resolution blade images, demonstrating improved accuracy in detecting tiny surface flaws by combining region filtering with a deep convolutional architecture [56]. Similarly, Li et al. introduces an improved YOLOv5 variant for real-time surface defect detection, using anchor tuning and an attention mechanism that boosts mean average precision to nearly 98.3% [26]. Beyond these application-specific approaches, Abdulrahman et al. offer a comprehensive review of deep learning techniques for aero-engine blade inspection, underscoring the consistent outperformance of modern methods over traditional machine vision algorithms [42].

In parallel, the growing body of research on transfer learning in industrial defect detection suggests that pre-trained models can enhance accuracy and robustness under data-scarce conditions. Liu et al. [57] apply transfer learning to small datasets of injection-molded products, achieving near-perfect detection accuracy by leveraging data augmentation and knowledge distillation from large-scale vision tasks. In the realm of casting and welding inspection, Ferguson et al. [58] demonstrate how combining Mask R-CNN with a multi-task transfer strategy can significantly reduce the volume of labeled training data needed while preserving high detection rates. A similar trend is evident in the work of

Abu et al. [59], who evaluated multiple architectures, including ResNet, VGG, DenseNet, and MobileNet, for steel surface defect detection, concluding that the choice of network and proper augmentation are critical for handling multi-class classification in industrial settings. Meanwhile, several studies have highlighted VGG19's potential for accurate feature extraction on challenging defect datasets. Wan et al. [29] designed a transfer learning-based approach for strip steel surface detection, revealing how freezing certain layers in VGG19 helps mitigate generalization problems arising from limited data. Madhavan et al. [60] explored the same architecture for radiographic weld inspection, attaining high precision by focusing on fine-tuning the network's deeper layers. Sun et al. [61] built upon transformer-based frameworks (i.e., DETR) to achieve high precision in aero-engine blade surface detection, leveraging attention modules that facilitate the modeling of non-local dependencies. Comparable findings appear in Vasan et al. [62], who investigated a vision transformer for steel surface anomalies and reported ~96.39% accuracy across multiple defect categories.

Broader industrial contexts support these observations. For example, Liu et al. 's [57] detailed approach to injection molding aligns with the insights from Ferguson et al. on casting defects [58], suggesting that transfer learning and carefully engineered deep models are central to reliable fault detection across different manufacturing domains. A similar methodology is confirmed by Abu et al. [59], whose experiments with multiple CNNs and small industrial datasets reinforce the utility of fine-tuning models. Moreover, Apostolopoulos and Tzani propose a multi-path version of the VGG19 network, illustrating how extra feature-fusion layers can further boost classification accuracy in general industrial defect scenarios [63,64]. Additional enhancements to vision transformers are observed in civil structural inspections, where Eltouny et al. [65,66] shows that carefully designed scaling networks can retain fine-grained details in large images without compromising computational feasibility. Even outside the traditional defect landscape, such as medical image analysis for eye disorders, VGG19 exhibits notable performance in identifying subtle features of faults [67]. These combined results underscore the growing consensus that both convolutional architectures (e.g., VGG19) and transformer-based approaches can be optimized—even with limited or unevenly distributed datasets—to yield robust, high-accuracy defect detection models across a broad range of industrial and research applications. Table 2 compares CNN-based methods with transformer-based approaches for defect detection, highlighting typical accuracy ranges, key benefits, and potential limitations.

Recent studies on automated defect detection in aero-engine components have predominantly relied on CNN-based architecture or shallow machine learning algorithms that do not fully capture complex texture variations. While models such as VGG19 have shown promising results, few investigations have systematically evaluated and contrasted these methods with the more recent transformer-based architecture, particularly in safety-critical aerospace contexts. Moreover, conventional transfer-learning approaches often freeze too many or too few layers, leading to suboptimal feature extraction in limited-data scenarios. These practices highlight a key gap in leveraging state-of-the-art transformers alongside optimal hyperparameter tuning strategies to ensure robust detection, especially when dealing with diverse defect classes and image quality variability.

Table 2. Comparison of CNN-based and transformer-based approaches for industrial defect detection, highlighting typical accuracy, key observations, and representative references.

Approach	Typical Performance & Observations	References
CNN-Based (e.g., YOLO, VGG19, Mask R-CNN, ...)	Generally, achieves ~80–99% accuracy for defect detection or classification in various industrial domains (aero-engine blades, strip steel, weld radiography, etc.). Performance benefits greatly from transfer learning, data augmentation, and proper hyperparameter tuning. CNNs are often faster to train but can miss subtle defects if not carefully fine-tuned or if data are limited.	[14,15,26,28–31,41–43,45,53,56–60,63,64,67]
Transformer-Based (e.g., DETR, vision transformer)	Commonly yields ~90–99% accuracy due to the self-attention mechanism's strength in capturing global context and fine-grained details. Particularly advantageous for large, high-resolution images and diverse defect types. However, these methods can be more resource-intensive, requiring greater computational power for training and inference.	[27,32–37,39,40,44,61,62,66]

To address these challenges, this paper applies and compares VGG19 and a DeiT (data-efficient image transformer) model under a unified, carefully controlled experimental design. We selectively freeze layers to fine-tune each model on the specialized aero-engine dataset, identifying the ideal transfer learning strategy using RandomSearchCV for hyperparameter optimization. In contrast to existing work, our approach offers (1) a rigorous head-to-head performance comparison between CNN and transformer architectures using standard accuracy, precision, recall, and AUC metrics; (2) UMAP-based visualization to illuminate how learned feature embeddings separate distinct defect types; and (3) an evidence-based demonstration that DeiT achieves a measurable performance boost (up to 7–10% higher accuracy and recall) over conventional CNN solutions. By systematically evaluating and refining both CNN- and transformer-based pipelines, this study contributes a novel roadmap for achieving more efficient and reliable defect detection in aero-engine components, with implications for greener, safer aviation practices.

2. Materials and Methods

Convolutional neural network (CNN): CNN belongs to a family of deep learning models intended for picture analysis. It is able to examine the images and interpret basic features, including, but not limited to, edges and textures. The layers of the network are composed such that they locate the relevant part of the image, compress the information, and, finally, encode the meaning of the whole picture into a single 'vector'. CNN models are commonly used to perform object detection in images. The most widely used CNN models are ResNet50, VGG16, and VGG19 [67]. Apart from the last two, which are layers that are fully connected, VGG19 is made up of nineteen fully connected layers and sixteen convolutional layers. Because it has been previously trained on the ImageNet dataset, it learns more about the multitude of images that it can see [68].

Vision transformer (ViT): ViT transforms the traditional usage of transformer architecture for visual tasks by breaking the image into patches and treating it as a sequence. These patches, which are highly processed to learn details as well as global features, are finally connected to a prediction layer. ViT models have also been demonstrated to be efficient for image recognition with configurations that consider the relationship between individual patches and the whole patch layout as well [33]. ViT-base-patch16-224 (pre-trained) considers an image as made of 16×16 pixel square patches and applies a transformer-based encoder to examine inter-patch relationships. It is pre-trained on the ImageNet dataset and thus has the capabilities of recognizing considerably diverse visual features, which, in turn, enhance its performance in image classification tasks [34].

Transfer learning: Transfer learning is an approach in which a model developed for a certain task is reused as a starting point for a model on a second task [69]. This method enables speed-up in the training phase as the model does not have to begin de novo and also minimizes the requirement for obtaining vast amounts of supervised data, which is expensive and time-consuming [70]. Since these models have developed an understanding of general concepts and spatial relationships, they can be further trained to do well on any specific task with only a few additional training examples. This attribute is exactly what makes transfer learning very important in conditions where there is limited data availability, as well as enhancing the efficiency and performance of the model [71].

Aero-engines are the major components of aviation technology, whereby flying from point A to B is carried out safely and efficiently. Inevitably, finding defects in aero-engine design and functionality is important as it helps ensure safety and operability. Incorporating artificial intelligence and machine learning into areas such as inspections, routine checks, and maintenance of aviation machines significantly enhances safety while reducing operational costs. AI-powered technologies have effectively inspected aero-engines so that small defects that may be difficult to see during inspections are not missed. Through image analysis and video, AI tools get to analyze overhead defects not visible to the human eye. Such computer vision algorithms have proved adequacy in the detection of issues in the engine parts; hence, problems or failures can be prevented or diagnosed at an early stage [72]. The other branch of artificial intelligence has to do with predictive maintenance, where historical records for maintenance inspections of parts of a machine are put into a machine learning algorithm, which can then predict how long a given component of an engine is likely to remain intact. This helps reduction in cases of unplanned unavailability of the aero-engines, thereby assisting greatly in enhancing the reliability and safety of the aero-engines [73]. Regarding this study, we target the finding of defects in aero-engines, which are integral components that enable flying safely and efficiently. We apply AI and ML technologies in inspecting engines to detect tiny defects that might go unnoticed in regular inspections.

Dataset: For this research, we utilized a specialized dataset from Kaggle specifically designed for detecting and identifying defects in aero-engines (https://www.kaggle.com/discussions/accomplishments/, accessed on 3 December 2024). The dataset consists of high-resolution images of turbine blades from different engine types, each carefully annotated with detailed information about the defects' location and nature. This structure allows for precise analysis and the application of machine learning algorithms for defect detection and predictive maintenance, ultimately enhancing the reliability and safety of aircraft engines. Figure 1 shows the samples of defects. To address the class imbalance in the dataset, class weights were calculated using the compute class weight function from scikit-learn [74].

These weights were incorporated into the loss function during training to ensure that the model treated all classes equitably, preventing it from favoring the more frequent classes.

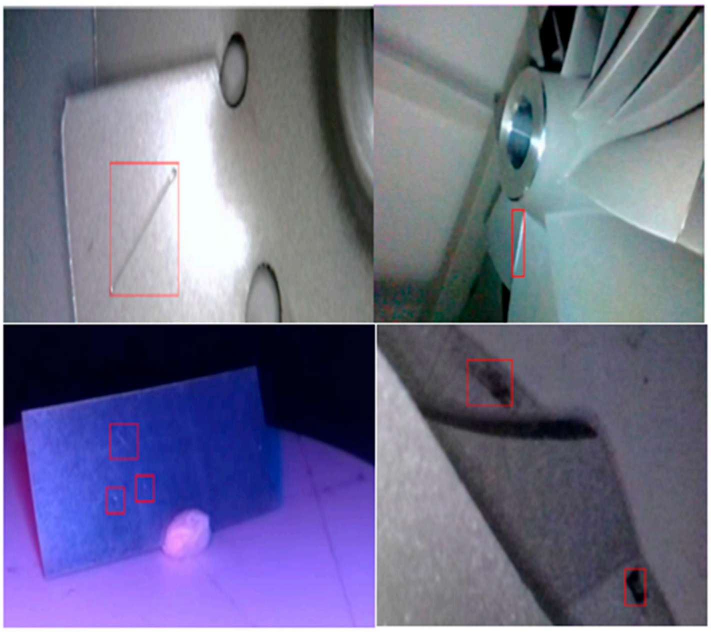

Figure 1. Samples of defects on aerospace engines, potential surface defects—such as scratches, cracks, and imperfections—on metal components.

Environment setup: The experimental setup was established using Python, incorporating key libraries such as PyTorch, torchvision, transformers, UMAP-learn, plotly, scikit-learn, and SHAP. These libraries were chosen for their strengths in deep learning, data augmentation, dimensionality reduction, and model interpretability. The environment was configured on a GPU-enabled machine to speed up model training.

Data augmentation and preprocessing: Data augmentation was employed to enhance the diversity of the training dataset and minimize the risk of overfitting. By artificially expanding the dataset, the model was exposed to a broader range of scenarios, helping to improve its generalization to unseen data. The augmentation pipeline included several key transformations aimed at altering the images while maintaining their crucial features. A key transformation was the Random Resized Crop, which resized each image to a random size and aspect ratio before cropping it to the model's required input size of 224 $\times$ 224 pixels. This technique helps the model handle varying image scales, enhancing its robustness to size variations. Additionally, Random Horizontal and Vertical Flips were applied, enabling the images to be flipped in both directions. This transformation mimics different viewing angles and orientations, which is especially helpful for capturing the natural variations found in real-world image data. To further increase diversity in the dataset, Random Rotation was employed to rotate the images within a $\pm$15-degree range. This adjustment helps the model remain unaffected by minor rotations that may occur in real-world situations. Another transformation applied in the pipeline was Color Jitter, which randomly adjusted the brightness, contrast, saturation, and hue of the images. These changes in color properties helped train the model to manage variations in lighting and color conditions typically encountered in different environments. Additionally, Random Grayscale was used to convert the images to grayscale with a certain probability, simulating different lighting conditions and ensuring the model could generalize across various color information. Finally, normalization was performed to standardize the images, adjusting the pixel values to a mean of [0.485, 0.456, 0.406] and a standard deviation of [0.229, 0.224, 0.225], aligning with the input requirements of the pre-trained models used in this study. This step is crucial for ensuring that the input data match the distribution expected by the models, facilitating effective learning. All of these transformations were implemented using the torchvision.transforms module and were consistently applied to both the training and validation sets. This consistency ensured that the model learned from a diverse yet standardized dataset, enhancing its performance on both seen and unseen data [75,76].

Feature extraction: Feature extraction is the process of transforming raw data into features or a set of features in such a way that their use optimizes multiple algorithms' performance in terms of accuracy and efficiency. It involves the selection and representation of the main attributes of the data and often entails data dimension reduction to the most prominent factors. In the case of an image, feature extraction methods perform the identification of edges, textures, shapes, and colors, which is essential for classification and recognition purposes. As indicated by Bengio et al. [77], feature extraction is one of the key conditions for success in working with deep learning models, as this operation makes it possible to create models that progressively incorporate the knowledge of structures within the data by passing through several layers, enhancing its generalization to novel tasks and datasets. The VGG19 model was selected for its deep convolutional layers to obtain feature representations of the images [30]. The classification layer was modified to achieve the elimination of the last fully connected layer such that the model was able to create embeddings appropriate for the tasks of classification that followed. Moreover, the last two layers of the model were modified to match the distinctive properties of the aero-engine defect dataset more closely. So, we used a DeiT model, which is based on the transformer architecture for image classification [34]. Like the previous approach, the DeiT model was also fine-tuned, but, in this case, it was only unfreezing the last few layers of its transformer encoder that allowed it to learn the features of the dataset. The model made sense of the images and created feature embeddings, which were used for categorical classification. These feature embeddings, once created by both models, were placed in a DataFrame and then were integrated with the associated class labels for the next steps of examination.

Dimensionality reduction and visualization: UMAP (Uniform Manifold Approximation and Projection) was employed for dimensionality reduction [78]. This reduced the high-dimensional feature space into two dimensions for ease of visualizing the distribution of the classes in the given dataset. The UMAP projections were shown in the form of scatter plots to bring out how well the classes could be discriminated against based on the features that were extracted.

Model training and hyperparameter tuning: The feature embeddings were classified by a specially developed neural network model. It was composed of dense layers with ReLU activation functions, dropout layers for regularization, and a SoftMax layer, which produced class probabilities. To improve the efficiency of the model, hyperparameter tuning was performed with RandomizedSearchCV, which set hidden layer sizes, a learning rate, dropout rate, and weight decay [79]. This process revolved around the search for the grid of parameters defined beforehand that would ensure the best possible metric performance of the configuration. Therefore, for the study, we used random search techniques to find out the most suitable hyperparameters for our model. The random search was conducted over a predefined space of hyperparameters, including the following: learning rate, weight decay, hidden layer sizes, and dropout rate. The best hyperparameters are shown in Table 3.

Table 3. Best hyperparameters and search ranges.

Hyperparameter	Search Area	Best Value
Weight Decay	$[1 \times 10^{-5}, 1 \times 10^{-4}, 1 \times 10^{-3}, 1 \times 10^{-2}]$	1×10^{-5}
Learning Rate (lr)	[0.001, 0.01, 0.1]	0.01
Hidden Size 1	[64, 128, 256]	128
Hidden Size 2	[128, 256, 512]	256
Dropout Rate	[0.2, 0.3, 0.5]	0.5

Cross-validation and model evaluation: The model's performance was evaluated using stratified K-fold cross-validation. This technique ensures each fold contains a balanced representation of all classes, reducing bias in the assessment. Metrics like accuracy, precision, recall, and ROC-AUC were measured, providing a comprehensive evaluation of the model's performance across different data splits [80].

Figure 2 shows the end-to-end workflow of our proposed aero-engine defect detection approach. It begins with data preparation and augmentation, followed by model initialization using either VGG19 or DeiT architectures. Next, we perform hyperparameter tuning using RandomizedSearchCV, implement K-fold cross-validation to evaluate and refine the models, and then conduct a final evaluation. Lastly, interpretability and visualization provide insights into model decisions and the learned representations.

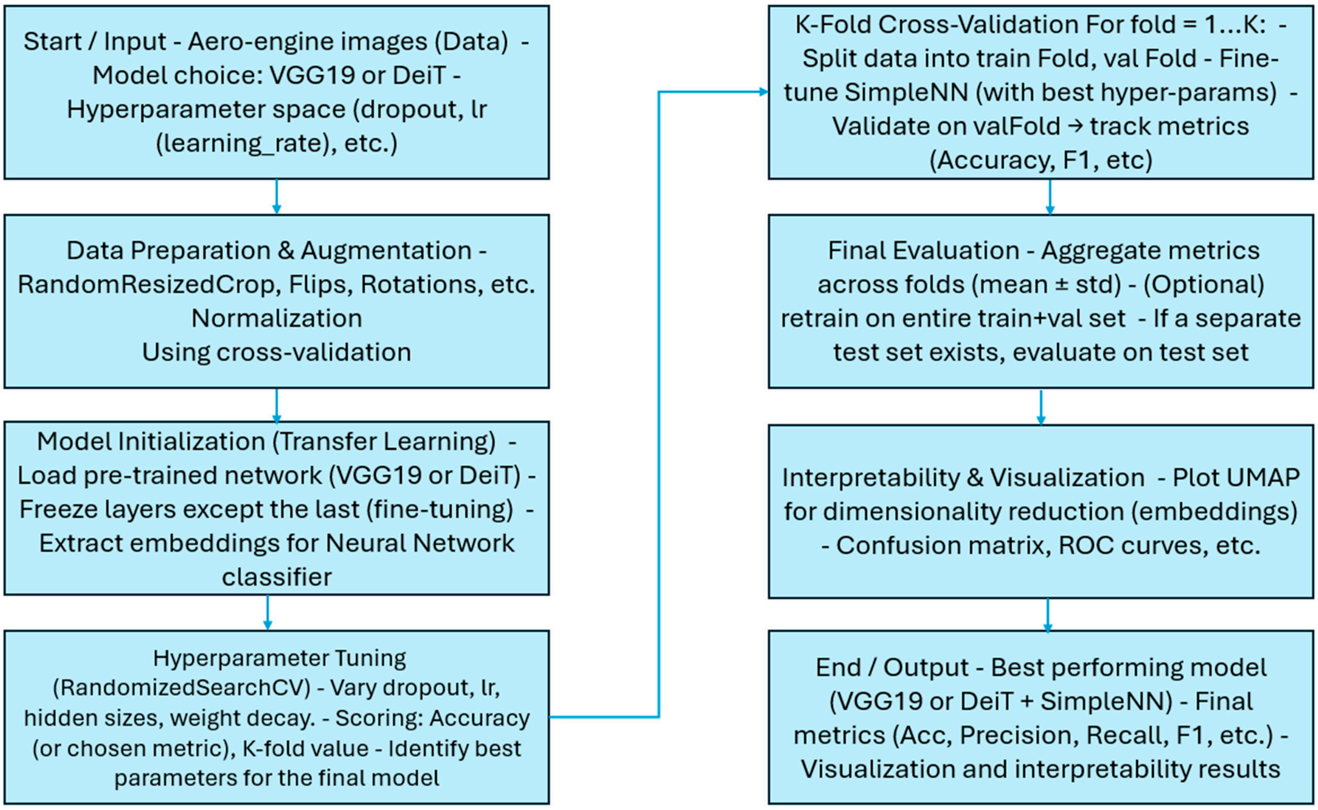

Figure 2. Overview of the proposed pipeline for aero-engine defect detection, illustrating data preparation, model initialization (VGG19 or DeiT), hyperparameter tuning, cross-validation, final evaluation, and interpretability/visualization steps.

3. Results

In this section, we present the UMAP projections of the embeddings from both the DeiT and VGG19 models. The UMAP projections of the embeddings of VGG19 and DeiT models are depicted in Figures 3a and 3b, respectively. For example, Figure 3a demonstrates the integration of UMAP and the embedding projections derived from the VGG19 model. The plot shows the distribution of the embeddings across damage feature classes, such as dot, scratch, crease, and damage. Similarly, Figure 3b illustrates the UMAP projection of the embeddings using the DeiT model, with the embeddings for the same set of defect classes (scratch, damage, crease, and dot) visualized. These figures provide a visual representation of how each model encodes the different classes within the embedding space.

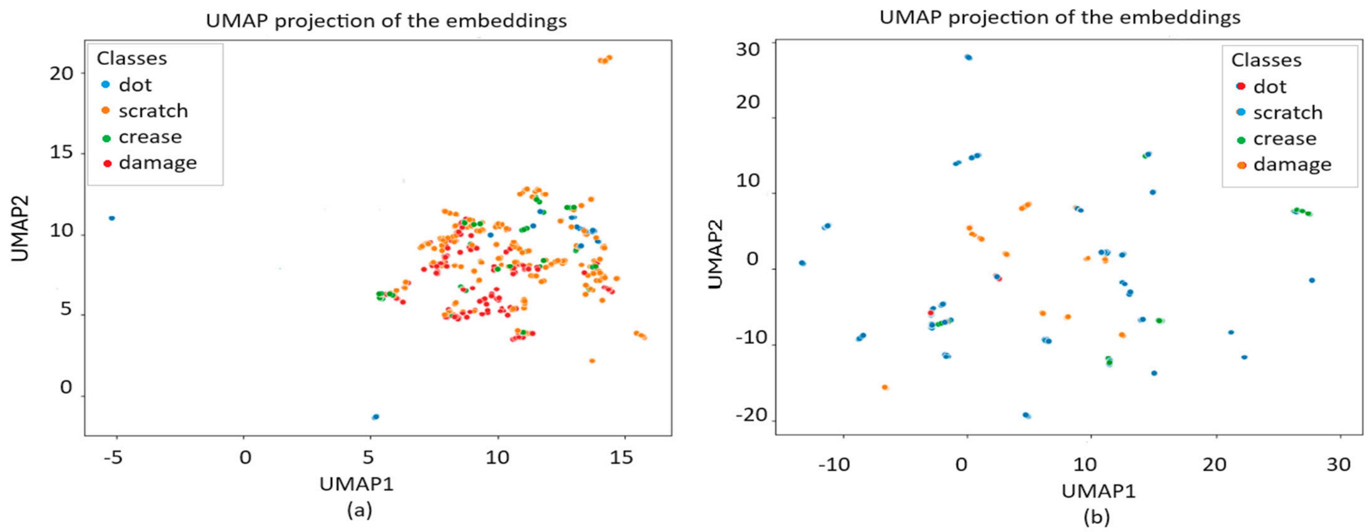

Figure 3. UMAP projections of embeddings: (**a**) VGG19, (**b**) DeiT.

We assessed the performance of two different deep learning models, VGG19 and DeiT, over ten training epochs, using various metrics: loss, accuracy, precision, and recall. The evaluation was conducted separately for both the training and validation datasets. The results are presented in Figure 4 and Table 4. The training phase for VGG19 showed a consistent decrease in loss from 1.796 to 0.354, demonstrating effective learning across epochs. The accuracy improved significantly from 31.36% in the first epoch to 80.49% by the tenth epoch. Similarly, precision and recall all exhibited upward trends, indicating improved predictive performance and reliability of the model over time. In the validation phase, the loss for VGG19 decreased from 1.054 to 0.590, and accuracy saw a steady increase, reaching up to 73.40% in the final epoch. For the DeiT model, the training metrics showed a sharp reduction in loss from 1.091 to 0.204, paired with a notable increase in accuracy from 59.77% to 88.19%. The precision and recall metrics showed a similar pattern, highlighting the model's growing ability to classify accurately and with minimal errors. Validation results for DeiT further confirmed its robustness, with loss tapering down from 0.606 to 0.244 and accuracy progressively climbing to 87.71% by the tenth epoch. Precision remained exceptionally high, showcasing the model's consistent performance.

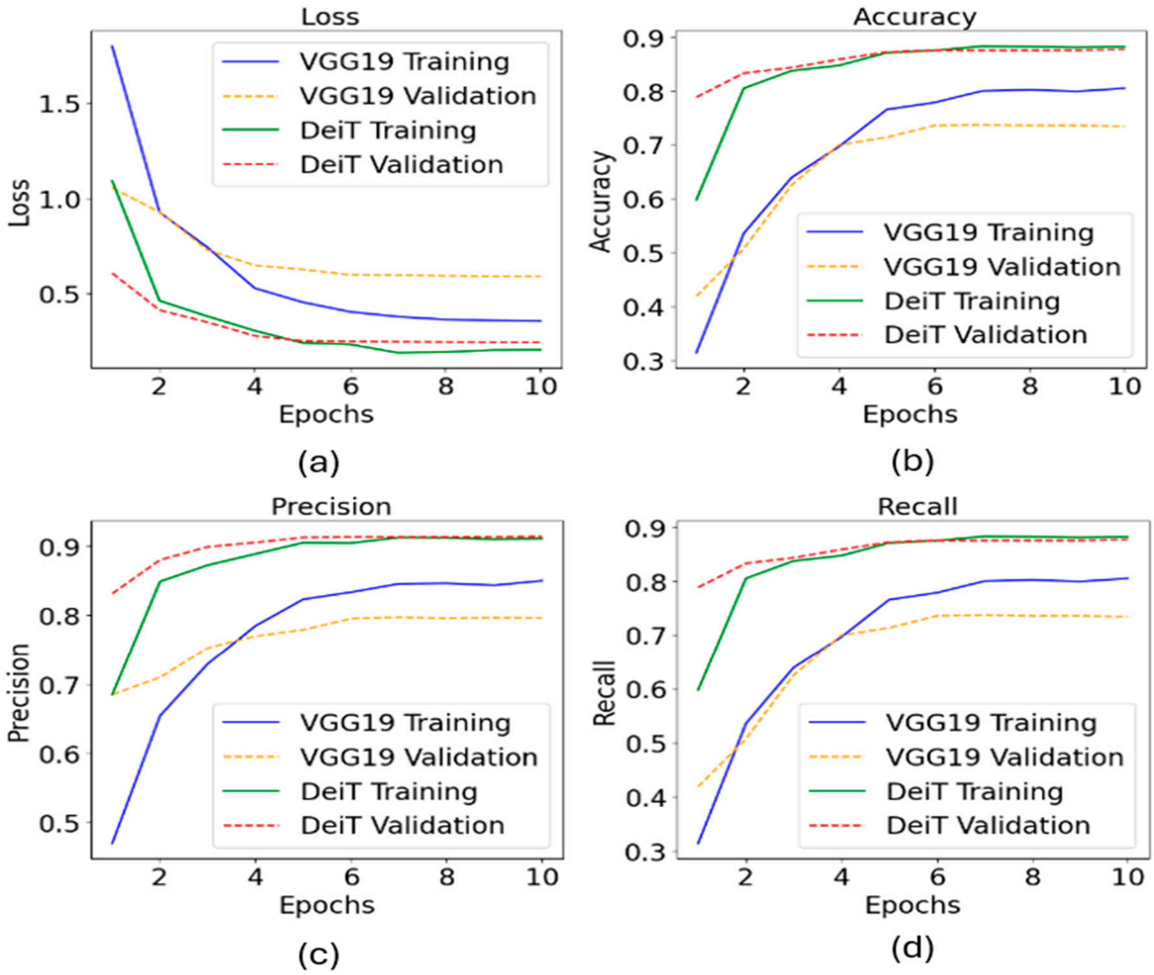

Figure 4. Comparative performance metrics for VGG19 and DeiT models: (**a**) loss over epochs; (**b**) accuracy over epochs; (**c**) precision over epochs; (**d**) recall over epochs.

Table 4. VGG19 vs. DeiT: metrics and performance comparison.

Model	Epoch	Loss (Train/Val)	Accuracy (Train/Val)	Precision (Train/Val)	Recall (Train/Val)
VGG19	1	1.7957/1.0539	0.3136/0.4185	0.4698/0.6847	0.3136/0.4185
VGG19	10	0.3541/0.5902	0.8049/0.7340	0.8498/0.7962	0.8049/0.7340
DeiT	1	1.0906/0.6063	0.5977/0.7883	0.6849/0.8314	0.5977/0.7883
DeiT	10	0.2037/0.2438	0.8819/0.8771	0.9110/0.9142	0.8819/0.8771

VGG19 ROC (Receiver Operation Characteristic) curve analysis: The ROC curves for the VGG19 model, as shown in Figure 5a, demonstrate the model's performance across four classes during the training and validation phases. The AUC (area under the curve) scores for the training sets are 0.85 for class 0, 0.97 for class 1, 0.93 for class 2, and 0.93 for class 3. In the validation sets, the AUC scores are slightly lower at 0.81 for class 0, 0.96 for class 1, 0.90 for class 2, and 0.90 for class 3. For the DeiT model, illustrated in Figure 5b, the ROC curves highlight consistent and high performance across all classes. The training phase AUC scores are impressive: 0.94 for class 0, 0.98 for class 1, 0.97 for class 2, and 0.99 for class 3. The validation phase maintains this high level of performance, with AUC scores of 0.95 for class 0, 0.98 for class 1, 0.97 for class 2, and 0.99 for class 3. These results showcase the DeiT model's exceptional ability to classify defects accurately across all evaluated classes.

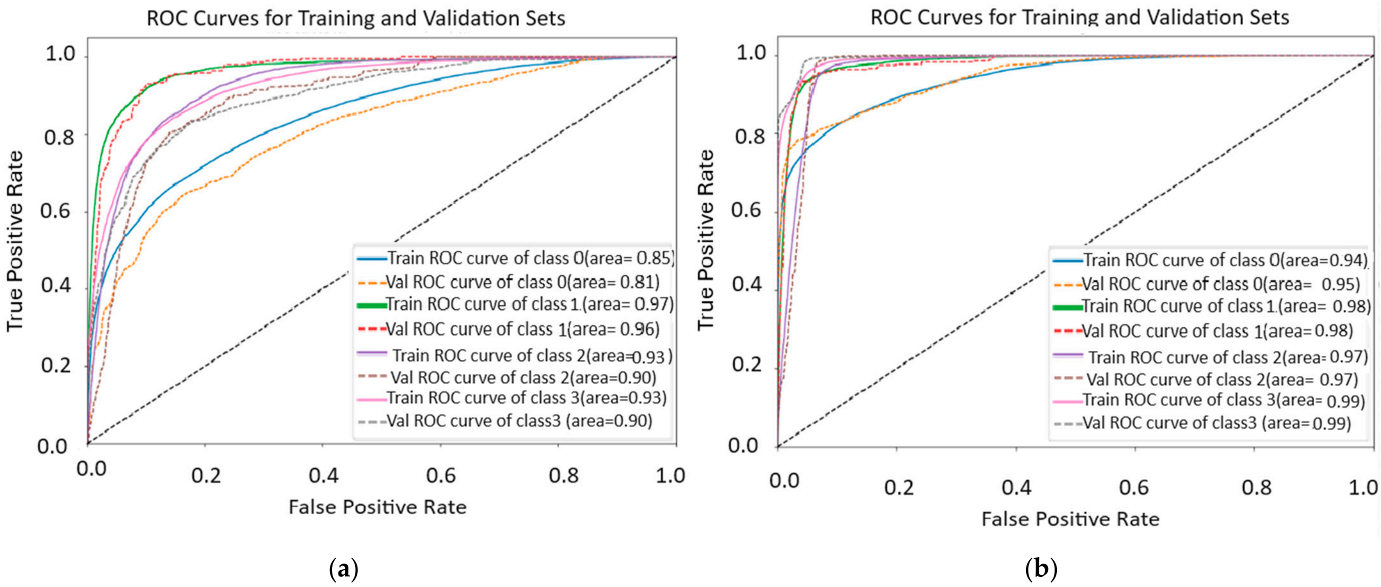

Figure 5. ROC curves of (**a**) VGG19 model and (**b**) DeiT model.

4. Discussion

The UMAP projections included in Figure 3a,b were helpful in understanding how VGG19 and DeiT models could classify the defect classes in accordance with the features they have learned. In the case of the VGG19 UMAP projection, some clustering of the defect classes, including dot, scratch, crease, and damage, is shown. However, there appears to be a noticeable overlap among the classes, particularly between scratch and crease. This could imply that VGG19 might have difficulty in differentiating some classes from others due to its ability to extract the necessary features being somewhat limited. This situation could be a consequence of the architecture of VGG19, where deep convolutional layers are used, and they are not always reliable in discriminating between classes. In contrast, the clustering of the defect classes in the UMAP projection for the DeiT model was more dispersed. The separation between classes appears to be less marked than the VGG19, which may suggest that DeiT may be picking up more general but unreliable spatial patterns of the classes. This could be because of the architecture of DeiT, which uses transformers to capture dependencies over long distances, which might result in class distinctions that are less clean-cut and more subtle. Figure 4 and Table 4 serve as a foundation for the discussion by providing a comparison of performance between VGG19 and DeiT models with respect to ten epochs and various performance metrics, such as loss, accuracy, precision, and recall. The interplay among the training data, validation dataset, and how each model forks out upon learning varies from one model to another.

Loss: The graphs show that there is a consistent decrease in loss in all epochs for both models, which is a good sign for any model in terms of training. VGG19, for instance, records a higher training loss at the first epoch at 1.7957, which later reduces to 0.3541 at epoch 10. On the other hand, with regards, conversely, to DeiT, it recorded a loss of 1.0906 and 0.2037 at the first and last epoch, respectively. The thicker line in the case of DeiT implies that the model is learning a great deal more, and this could be due to the model architecture of the transformer, which seems to be able to learn intricate features and relationships in the dataset.

Accuracy: DeiT has a rate of performance that is above that of VGG19, and this trend is observed in the model throughout the training. Accuracies in VGG19 began at 31.36% and improved to 80.49%, while the figures for DeiT started at 59.77% before reaching 88.19% at the end of its training. The higher starting accuracy for DeiT could signify that due to its architecture, the model is able to extract the required features well enough even before completing the initial phases of the training, resulting in better overall performance during the training.

Precision and recall: The other distinctive trends when comparing the two models are the trends in precision and recall. For the case of VGG19, precision goes up from 0.4698 to 0.8498, and recall rises from 0.3136 to 0.8049, indicating consistent improvement. On the other hand, DeiT performs better, as precision increases from 0.6849 to 0.9110 and recall increases from 0.5977 to 0.8819. The better performance of DeiT in these metrics can be attributed to its architecture, which makes it possible to attain a higher performance of the respective defect classes with great accuracy.

The similarities regarding the training and validation metrics in both models imply that the models are able to perform well with different splits of data. The results achieved using DeiT seem to suggest that there is a steady increase in score across all metrics, and perhaps this is due to the strength of the transformer architecture used. VGG19 also shows significant improvements, for example, in precision and recall values, and this indicates that it is able to learn and recognize the defective classes very well. The comparison presented in Figure 4 and Table 2 clearly demonstrates the advantages of DeiT in terms of learning speed, generalization, and performance on the model metrics. This contrasts with VGG19, which, though good and showing considerable improvement, may take longer to achieve the same performance because of the differences in the architecture of the two models. These results support the conclusion that DeiT's transformer-based technology may offer potential advantages for operations requiring more accurate and robust defect classification.

The ROC curves of VGG19 and DeiT, as illustrated in Figure 5, allow further assessment of each model's ability to classify the different defect classes. The ROC curves for VGG19 indicate that there was an anticipated achievement of between 0.85 and 0.93 AUC scores during the training of the network. However, the AUC figures were somewhat lower than expected, especially the AUC of class 0, which fell from 0.85 to 0.81 on average. This drop in performance might suggest that the VGG19 model is struggling to generalize on unseen data and, therefore, might be overfitting the training data. The deeper network might be learning some of the noise variants as well as useful features, which affects its performance on the testing datasets. The ROC curves for DeiT are satisfactory, with an AUC score of 0.95 and great reach across the targeted goal across the training set and validation set. Perhaps this could suggest that the adaptive transformer architecture in DeiT does equip the model to generalize well on challenging unseen data when classifying different classes. The high AUC measures have been indicative that the defect classification tasks that are performed by DeiT are likely to be more accurate, robust, and reproducible.

5. Conclusions

The focus of this work was on the application of transfer learning techniques for the purposes of enhancing the generalization of deep learning models for the aero-engine defect detection task. The idea behind transfer learning was to utilize models that had already been trained so that meaningful features could be extracted from them using only a small amount of training on a limited dataset. For transfer learning purposes, the models were first tuned using the RandomSearchCV to adjust the learning parameters, and partially frozen layers were used for the length of the model to ensure that learned features were kept and that the model's application to a new function was possible. Our comparative analysis suggested that the main parameters of the DeiT model were better than the VGG19 model in terms of metrics such as accuracy, precision, and recall. Among various reasons, this performance can be attributed to DeiT's transformer-based architecture, which is relatively outstanding in complex pattern recognition of the data. Although there were some significant enhancements with VGG19 as well, the performance metrics of VGG19 showed weaker performance than the DeiT model.

Apart from aiding in the achievements of the detection of defects, this research focuses on the broader use of such developments in terms of improving the efficiency of aviation operations. The use of deep learning networks, such as DeiT, for defect detection may enhance maintenance regimes and consequently cut maintenance time. This is consistent with green aviation objectives, since it assists in achieving robust engine performance in-field. In subsequent works, perhaps more advanced approaches, such as unsupervised learning or domain adaptation, might be tested to make the model more robust. Moreover, the problems faced in this work could be solved with the use of alternative model configurations or by including different sources of data that could enhance defect detection in aerospace systems.

In the future, several further enhancement actions would bolster the contributions of this work to the real world and broaden the scope of practical applicability under actual aero-engine environments. First, their application for borescope inspection, integrating the proposed system, means that the pictures are taken on the wing or at MRO (Maintenance, Repair, and Overhaul) facilities, which would test the system under various light, angle, and operational parameters. Second, expanding the types of defects to include rub-tipping, erosion, and frond object damage would increase the generalizability and ensure that the method addresses a larger proportion of engine abnormalities. Third, with regard to the domain adaptation methods, the success of the research dataset and the operational engine image is achieved with minimal loss of accuracy even though the images are taken under different conditions. Finally, the introduction of semi- or unsupervised learning may ease the burden of labeling data but preserve a high detection rate in industrial circumstances involving a sole feature of intricate or little data, which is of great significance. Following these developments, the suggested framework is expected to be closer to large-scale applications, thereby improving the predictive maintenance approaches, reducing operational expenses, and reinforcing the security and environmentally friendly principles of the aerospace industry.

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