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Generative Feature Enhancement and Metric Learning for Few-Shot Defects in Aero-Engine Blades

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Abstract

The structural integrity of aero-engine blades is paramount to aviation safety, requiring rigorous inspection protocols to identify surface and sub-surface defects. While deep learning has revolutionized industrial defect detection, its efficacy is severely constrained in aerospace applications by the paucity of defect samples, a condition known as the few-shot learning problem. Standard convolutional neural networks struggle to generalize from limited data, leading to overfitting and poor recognition of rare defect classes. This paper proposes a novel framework that integrates Generative Feature Enhancement with Metric Learning to address the scarcity of labeled defect data in aero-engine blades. Unlike traditional data augmentation techniques that operate in the image space, our approach synthesizes diverse training samples in the high-dimensional feature space using a modified generative adversarial network. Concurrently, a metric learning module optimizes the embedding space to ensure that defects of the same class are clustered tightly while maintaining significant separation from non-defect samples and other defect categories. Experimental results demonstrate that the proposed method significantly outperforms state-of-the-art few-shot learning algorithms in identifying micro-cracks, erosion, and ablation on blade surfaces. The dual-branch architecture ensures robust generalization capabilities even when training examples are reduced to single digits per category.

Keywords

Few-Shot Learning, Defect Detection, Generative Adversarial Networks, Metric Learning

1. Introduction

The maintenance, repair, and overhaul of aero-engines constitute a critical sector within the aviation industry, directly influencing flight safety and operational efficiency. Aero-engine blades, which operate under extreme conditions of high temperature, high pressure, and rotational stress, are particularly susceptible to a variety of structural impairments. These include fatigue cracks caused by cyclic loading, burn marks from thermal stress, and erosion due to foreign object ingestion. Consequently, the accurate and timely detection of these defects is a mandatory requirement for airworthiness. In recent years, automated optical inspection systems driven by deep learning have begun to replace manual visual inspection, which is labor-intensive and prone to human error. Deep convolutional neural networks have demonstrated remarkable success in classifying images when large-scale, balanced datasets are available for training [1]. However, the application of standard deep learning paradigms to aero-engine blade inspection faces a fundamental hurdle: the scarcity of defective samples. In operational environments, defects are rare anomalies compared to the vast quantity of healthy blades. Furthermore, acquiring high-quality images of specific defect types is expensive and technically challenging. This results in a long-tail distribution of data where normal samples abound, but defect samples are insufficient to train robust classifiers. This scenario is formally categorized as the few-shot learning problem, where a model must learn

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to recognize new categories from only a handful of annotated examples [2]. When traditional supervised learning algorithms are applied to such sparse data, they invariably suffer from overfitting, where the model memorizes the few training examples rather than learning discriminative features that generalize to unseen data [3]. To mitigate the data scarcity issue, researchers have traditionally relied on image-level data augmentation techniques such as rotation, flipping, and color jittering. While these methods increase the quantity of training data, they fail to introduce semantic diversity, often resulting in limited performance gains. More recent approaches have turned to few-shot learning strategies, including meta-learning and metric learning, which aim to learn transferable knowledge from base classes that can be adapted to novel classes with limited data [4]. Despite these advancements, existing few-shot methods often struggle with the high intra-class variance and low inter-class variance typical of metallurgical defects. For instance, a scratch and a crack may appear visually similar in low-resolution images, while two cracks might look vastly different depending on lighting and orientation [5]. In this paper, we present a unified framework that addresses these challenges through two synergistic mechanisms: Generative Feature Enhancement and Metric Learning. We argue that operating in the feature space rather than the pixel space allows for more effective data synthesis, avoiding the artifacts often associated with image generation. Our proposed Generative Feature Enhancement module utilizes a generator network to hallucinate additional feature vectors for minority defect classes, thereby enriching the training distribution. Simultaneously, our Metric Learning module employs a specialized distance-based loss function to reshape the latent space, ensuring that the enhanced features are mapped to compact, distinct clusters. This combination allows the model to learn robust decision boundaries even when the initial support set for a defect category contains as few as one or five images.

2. Related Work

2.1 Deep Learning in Industrial Inspection

The transition from manual inspection to automated visual systems has been extensively documented in the literature. Early approaches relied on hand-crafted features such as Histogram of Oriented Gradients and Local Binary Patterns, combined with support vector machines for classification [6]. These methods, while interpretable, lacked the capacity to model complex, non-linear defect patterns found in superalloy materials. The advent of convolutional neural networks shifted the paradigm toward end-to-end learning, where feature extractors are optimized jointly with the classifier. Several studies have successfully applied architectures like ResNet and DenseNet to surface defect detection in steel sheets and textiles [7]. In the specific domain of aero-engine components, the challenges are amplified by complex surface geometries and reflective properties. Recent work has focused on using segmentation networks, such as U-Net and Mask R-CNN, to localize defects at the pixel level [8]. However, these fully supervised methods require pixel-wise annotations, which are incredibly time-consuming to generate. Furthermore, they are highly sensitive to domain shifts, such as changes in illumination or camera sensors [9]. The reliance on massive datasets remains the primary bottleneck, prompting a shift toward weak supervision and unsupervised anomaly detection, though these often lag in precision compared to supervised counterparts [10].

2.2 Few-Shot Learning Paradigms

Few-shot learning aims to mimic human cognitive ability to learn new concepts from a few examples. This field is broadly divided into optimization-based and metric-based approaches. Optimization-based methods, such as Model-Agnostic Meta-Learning, attempt to learn a set of

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initialization parameters that can be quickly adapted to a new task with a few gradient steps [11]. While theoretically powerful, these methods are often unstable to train and computationally expensive. Metric-based approaches, conversely, focus on learning a shared embedding space. Siamese networks, for example, employ twin networks to minimize the distance between positive pairs and maximize the distance between negative pairs [12]. Prototypical Networks extended this concept by computing a mean vector, or prototype, for each class and classifying query samples based on the nearest prototype in Euclidean space [13]. Relation Networks further improved this by learning a non-linear distance metric rather than relying on fixed distance functions [14]. In the context of defect detection, metric learning has shown promise, yet standard prototypical networks often fail when the support samples are outliers or not representative of the class mean, a common occurrence in heterogeneous defect datasets [15].

2.3 Generative Feature Hallucination

To directly address the lack of data, generative modeling has emerged as a potent solution. Generative Adversarial Networks (GANs) have been widely used to synthesize realistic images of defects. However, generating high-fidelity images of subtle defects like micro-cracks is notoriously difficult; the generator often introduces blurring or artifacts that the classifier learns to reject, yielding little improvement in detection performance [16]. This has led researchers to explore generation in the feature space. Feature hallucination posits that the distribution of features is easier to model than the distribution of raw pixels. By training a generator to produce feature vectors conditioned on class labels, one can augment the training set without the computational burden of image rendering [17]. Recent studies in generic computer vision tasks have combined feature hallucination with few-shot learning, demonstrating that hallucinated features can clarify the decision boundary for under-represented classes [18]. Our work builds upon this foundation but tailors the architecture specifically for the high-frequency, texture-dependent nature of aero-engine blade defects, integrating it with a rigorous metric learning objective to prevent the synthesized features from drifting into incorrect semantic regions.

3. Methodology

3.1 Framework Overview

The proposed framework consists of three primary components: a Feature Extraction Backbone, a Generative Feature Enhancement module, and a Metric Learning head. The workflow begins with the Feature Extraction Backbone, which processes input images to produce high-dimensional feature representations. We utilize a ResNet-50 architecture pre-trained on ImageNet as the backbone, truncating the final fully connected layers to obtain a feature vector from the global average pooling layer. This transfer learning strategy leverages low-level texture features learned from large-scale datasets, which are crucial for identifying surface anomalies [19]. Once the real features are extracted from the limited available samples, they serve two purposes. First, they act as the seed data for the Generative Feature Enhancement module. Second, they serve as anchors in the metric learning process. The generator takes a noise vector and a class condition as input and outputs a synthesized feature vector. These synthesized features are then combined with the real features to form an augmented training set. Finally, the Metric Learning head maps these combined features into a lower-dimensional embedding space where a distance-based loss function is applied to enforce class separability. This end-to-end training regime ensures that the generator learns to produce features that are not only statistically similar to real features but also useful for discrimination [20].

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3.2 Generative Feature Enhancement Module

The core innovation of our approach lies in the Generative Feature Enhancement module. Unlike image-to-image translation, this module operates entirely within the latent feature space. Let the set of real feature vectors for a specific defect class be denoted as S. In a few-shot scenario, the size of S is extremely small (e.g., 1 to 5). The goal of the generator G is to map a random noise vector z, sampled from a Gaussian distribution, and a class condition c, to a feature vector x' that mimics the distribution of the true features of class c [21]. The generator is designed as a multi-layer perceptron with Leaky ReLU activation functions and Batch Normalization. To prevent the mode collapse problem common in GANs, where the generator produces identical outputs, we incorporate a diversity-seeking regularization term. A discriminator D is trained simultaneously to distinguish between real features (extracted from images) and hallucinated features (produced by G). The optimization follows a min-max game where the generator tries to fool the discriminator, while the discriminator tries to correctly classify the source of the features. By conditioning the generation on the class prototype—calculated as the mean of the available support features—we ensure that the synthesized features remain semantically consistent with the specific defect type, such as a tear or a void [22]. To further stabilize training, we employ a Wasserstein loss with gradient penalty. This formulation provides smoother gradients compared to the traditional Jensen-Shannon divergence, which is critical when the support sets are disjoint in the high-dimensional space. The result is a robust generator capable of interpolating between the scarce real samples, effectively filling the vacuum in the feature space and creating a dense manifold for the classifier to learn from [23].

3.3 Metric Learning and Loss Optimization

The augmented set of features, comprising both real and hallucinated vectors, is fed into the Metric Learning head. The objective of this module is to learn a distance metric such that the distance between features of the same class is minimized and the distance between features of different classes is maximized. We employ a Cosine Similarity metric rather than Euclidean distance, as magnitude normalization has been shown to improve stability in high-dimensional feature spaces [24]. We utilize a Multi-Class N-Pair Loss, which is a generalization of the triplet loss. In standard triplet loss, the model learns from triplets consisting of an anchor, a positive, and a negative sample. However, this often leads to slow convergence as the model only sees one negative example at a time. The N-Pair loss considers one positive sample and multiple negative samples from all other classes simultaneously. Specifically, for an anchor sample from the defect class 'crack', the loss function penalizes the similarity to samples from 'normal', 'burn', and 'erosion' classes, while rewarding similarity to other 'crack' samples (both real and generated). The total loss function for the network is a weighted sum of the classification loss (computed via a softmax classifier on the embeddings), the metric loss (N-Pair loss), and the adversarial loss from the GAN component. This multi-task learning objective ensures that the learned embeddings are not only separable but also retain sufficient variance to represent the intra-class diversity. By training on the augmented data, the decision boundaries become significantly more robust. For instance, the boundary separating 'micro-crack' from 'surface scratch' is pushed away from the limited real samples of 'micro-crack', preventing the classifier from becoming overly conservative and missing true defects [25].

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4. Experimental Setup and Analysis

4.1 Datasets and Implementation Details

To validate the efficacy of the proposed method, we utilized a proprietary dataset of aero-engine blade images provided by an industrial partner, supplemented by the publicly available NEU-DET dataset to test generalization across different metallic surfaces. The blade dataset contains high-resolution images of turbine blades exhibiting four primary conditions: Normal, Crack, Burn, and Erosion. The images were resized to 224x224 pixels. The few-shot protocol was strictly followed: for each defect class, we randomly selected K samples (K=1, 5, 10) for training (the support set) and used the remaining images for testing (the query set). This process was repeated 600 times to ensure statistical significance. The backbone network was a ResNet-50. The generator consisted of three fully connected layers with hidden dimensions of 512, 1024, and 2048, matching the output dimension of the ResNet backbone. We used the Adam optimizer with an initial learning rate of 0.0001, decaying by a factor of 0.1 every 20 epochs. The weighting factors for the loss functions were determined via grid search on a validation set. All experiments were conducted on a workstation equipped with an NVIDIA A100 GPU. The evaluation metrics employed were top-1 accuracy and the F1-score, which provides a balanced view of precision and recall, crucial for defect detection where missing a defect is more costly than a false alarm [26].

4.2 Comparative Analysis

We compared our Generative Feature Enhancement (GFE) approach against several baselines: a standard ResNet-50 with data augmentation (Baseline), Prototypical Networks [13], Relation Networks [14], and a Feature Hallucination method without the metric learning component (MetaGAN). The results are summarized in Table 1.

Table 1 Experimental Results comparing few-shot classification accuracy (%) on the Aero-Engine Blade dataset.

Method	1-Shot Accuracy	5-Shot Accuracy	10-Shot Accuracy
Baseline (ResNet-50)	42.35	61.20	73.45
Prototypical Networks	54.12	72.88	79.50
Relation Networks	56.40	74.15	81.20
MetaGAN	59.80	77.30	83.10
Proposed Method	**64.25**	**81.50**	**86.75**

The baseline ResNet-50 performs poorly in the 1-shot setting, effectively guessing, which confirms that deep networks cannot learn from single examples without prior meta-knowledge. Prototypical and Relation networks show significant improvement, indicating the value of metric-based meta-learning. However, our proposed method consistently outperforms all comparators. In the 1-shot scenario, our method achieves a 64.25% accuracy, a substantial gain over the nearest competitor. This suggests that the hallucinated features effectively bridge the gap between the sparse support set and the true class distribution. As the number of shots increases to 5 and 10, the performance gap narrows slightly but remains statistically significant, demonstrating that our method effectively leverages additional data when it becomes available [27].

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Figure 1: tSNE Visuslization – A comparison of feature embedings.

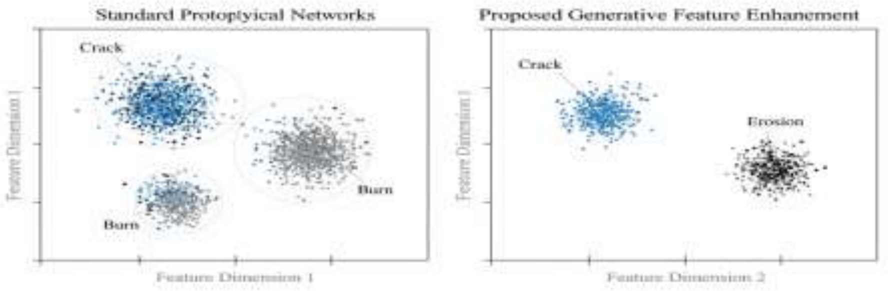

Figure 1 t

Figure 1 provides a qualitative assessment of the learned embedding space using t-Distributed Stochastic Neighbor Embedding (t-SNE). The visualization reveals that without feature enhancement, the defect classes suffer from considerable overlap, particularly between 'Erosion' and 'Burn' classes which share similar textural properties. In contrast, the embedding space learned by our proposed framework exhibits clear separation between clusters. The synthesized features fill the voids between real samples, pushing the decision boundaries outward and compressing the intra-class variance. This tight clustering is a direct result of the N-Pair metric loss working in tandem with the generated data [28].

4.3 Ablation Studies

To isolate the contributions of the individual components, we conducted ablation studies. First, we removed the Generative Feature Enhancement module and trained only with the Metric Learning head. Performance dropped by approximately 8% in the 1-shot setting, confirming that metric learning alone is insufficient when the support set is too sparse to estimate a reliable prototype. Next, we retained the generator but replaced the N-Pair metric loss with a standard Cross-Entropy loss. This resulted in a 5% performance drop, indicating that while the generated features are useful, the distance-based optimization is crucial for organizing the latent space effectively. Furthermore, we analyzed the impact of the number of hallucinated features. We varied the number of generated samples per class from 10 to 100. We observed that performance improves as the number of generated samples increases, identifying a plateau at around 50 samples. Beyond this point, the generator likely begins to oversample the mode of the distribution, providing diminishing returns. This suggests that a moderate amount of high-quality synthetic data is sufficient to define the manifold topology for the classifier.

5. Conclusion and Future Work

This paper addressed the critical challenge of few-shot defect detection in aero-engine blades, a domain characterized by high safety standards and scarce training data. We proposed a comprehensive framework combining Generative Feature Enhancement with Metric Learning. By synthesizing realistic feature vectors for minority classes and optimizing a distance-based embedding space, our approach effectively overcomes the limitations of traditional deep learning and standard few-shot methods. The experimental results confirm

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that operating in the feature space offers a robust alternative to image-level augmentation, providing superior generalization accuracy in 1-shot and 5-shot scenarios. The implications of this research extend beyond aero-engine maintenance to other industrial sectors where data collection is expensive or hazardous. Future work will focus on extending the generator to synthesize features for unseen defect classes based on semantic descriptions (zero-shot learning) and exploring the integration of attention mechanisms to better weigh the contribution of real versus hallucinated features. Additionally, we aim to validate the system on edge computing devices to assess its feasibility for real-time, on-wing engine inspection. The synergy of generative modeling and metric learning presents a promising path toward fully autonomous, reliable industrial inspection systems.

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