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Artificial-Intelligence-Empowered Optimization and Intelligent Recognition of Non-Destructive Testing Technology

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Abstract: As high-end manufacturing imposes increasingly stringent requirements on component quality, conventional non-destructive testing (NDT) encounters difficulties in massive-data interpretation, micro-defect identification, and quantitative evaluation. The penetration of artificial intelligence into non-destructive testing technologies creates a new paradigm for technical improvement and intelligent recognition in NDT. This paper discusses the subject from two perspectives: optimization paths and recognition strategies. It improves the end-to-end efficiency of the whole testing chain through four approaches: data augmentation, lightweight models together with edge acceleration, physics-informed fusion imaging, and end-to-end workflow reconstruction. On the recognition dimension, it puts forward strategies including transfer-learning-based few-shot defect recognition, multi-modal attention-fusion-enabled grading, explainability-assisted quantitative assessment, and online continual-learning-driven predictive health management.

Keywords: Non-destructive testing; Artificial intelligence; Deep learning; Intelligent defect recognition; Optimization path

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1. Introduction

Non-destructive testing serves as a critical technology for guaranteeing the structural integrity of key components in aerospace, energy and power, rail transit, and other sectors. Nevertheless, traditional methods such as ultrasonic testing, radiographic testing and eddy-current testing generate large volumes of waveform, image and sequence data. Defect judgment largely relies on expert experience, bringing about problems including low testing efficiency, strong subjectivity, and frequent missed detection of micro-defects. Especially for complex backgrounds and evolving damages, manual recognition can hardly satisfy industrial demands in terms of quantitative consistency and real-time performance [1]. In recent years, artificial-intelligence technologies represented by convolutional neural networks and Transformers have

presented powerful capabilities for automatic feature extraction and pattern recognition, offering a new solution to the above-mentioned challenges. Artificial intelligence can enhance fundamental links such as signal acquisition and image reconstruction, and render defect recognition more accurate and explainable.

2. Optimization paths for artificial-intelligence-empowered non-destructive testing technology

2.1. Enhancement and intelligent cleaning optimization of multi-source heterogeneous testing data

Non-destructive-testing data are multi-sourced, including ultrasonic A/B/C-scan data, infrared thermograms, digital radiographic images, and so forth. Such data suffer from severe noise interference, severe sample-category imbalance, and scarcity of high-quality annotations. Improvements at the data-source level can boost the performance of artificial-intelligence models.

First, in terms of data expansion, conventional augmentation methods such as rotation, scaling, and elastic deformation, together with generative adversarial networks, are adopted to generate realistic defect samples so as to expand rare-category samples such as cracks and incomplete fusion. For instance, StyleGAN can be leveraged to produce images of internal weld pores, which remarkably improves the model's generalization capacity for few-shot defects. Second, deep denoising approaches including convolutional auto-encoders and non-local means are applied to implement intelligent cleaning for ultrasonic echoes or radiographic images. They eliminate structural noise while preserving faint defect features and improve the signal-to-noise ratio [2]. Furthermore, for annotation optimization, active learning and semi-supervised learning are adopted. Active learning enables the model to screen the most informative unlabeled samples for expert annotation, so as to minimize data costs and maximize data value. Semi-supervised learning combines a small set of precise annotations with abundant unlabeled data and enhances learning efficiency via consistency regularization [3]. Multi-angle coordinated data augmentation and cleaning build a favorable data foundation for subsequent model training and recognition.

2.2. Deep-learning-model lightweighting and edge-side accelerated inference

Industrial sites set high requirements for real-time performance and portability of testing. Nevertheless, huge parameter volumes and complicated computation of deep networks frequently become deployment barriers. Improving inference speed by means of model lightweighting and hardware acceleration constitutes a vital part of optimization paths. On the architectural-design level, lightweight backbone networks (MobileNet, ShuffleNet) adopting depth-wise separable convolutions and inverted residual structures, or neural-architecture-search techniques for automatic design of efficient networks, greatly reduce parameter quantities while maintaining relatively high recognition accuracy [4]. Model-compression technologies include unstructured pruning for removing redundant connections, structured pruning for direct channel-number reduction, and 32-bit-floating-point-to-8-bit-integer parameter quantization. Then inference-optimization tools such as TensorRT and OpenVINO are utilized to realize millisecond-level forward computation on embedded GPUs or FPGAs [5]. Knowledge distillation employs high-precision teacher models to guide lightweight student models, so as to mitigate accuracy loss caused by compression.

2.3. Imaging optimization via hybrid physical-model-and-data-driven approaches

Advanced NDT imaging methods such as ultrasonic phased-array total-focus-method imaging and infrared lock-in thermography can deliver abundant information, yet conventional reconstruction algorithms are plagued by long computation time or limited resolution. Combining artificial intelligence with physical models can jointly optimize imaging quality and speed. Take data acquired via ultrasonic full-matrix capture as an example: the conventional delay-and-sum method requires excessive point-by-point computation. In contrast, fully convolutional networks directly map multi-channel raw data to high-resolution reconstructed images, shortening imaging time by an order of magnitude and compensating for artifacts induced by beam divergence and anisotropy [6]. For X-ray or infrared images, super-resolution generative adversarial networks can refine details of low-resolution raw images and render tiny fatigue cracks more distinguishable.

2.4. Automatic feature extraction and reconstruction of end-to-end testing pipelines

Traditional non-destructive testing workflows are generally divided into three parts: pre-processing, manual feature design, and classifier training. Each part is optimized separately and heavily depends on expert experience. Empowered by artificial intelligence, end-to-end deep-learning architectures directly map original signals to defect-judgment results, break down module barriers, and make global optimization feasible [7]. For acoustic-emission waveforms, one-dimensional fully convolutional networks or Transformers directly process long-time sequences to output defect-location and category labels. For X-ray weld images, end-to-end detectors such as YOLO and DETR accomplish defect recognition and precise bounding-box regression simultaneously [8]. Furthermore, reinforcement learning can adaptively adjust scanning paths of ultrasonic probes. Faced with irregular and complicated geometric shapes, it adaptively expands the testing scope and accordingly reduces mechanical-scanning blind zones.

3. Effective strategies for artificial-intelligence-empowered intelligent recognition of non-destructive-testing technology

3.1. Few-shot defect-recognition strategy based on deep transfer learning

In practical engineering, severe-defect samples are hard to obtain, and annotation requires multiple experts, resulting in limited available data volumes. Conventional deep-learning approaches are prone to overfitting under such circumstances. Deep transfer learning offers an important breakthrough. After pre-training on large-scale natural-image datasets (e.g., ImageNet) or physical-simulation datasets, models learn many general features, including textures and geometries. Then only a small number of real defect samples are needed for fine-tuning so that models can rapidly adapt to target detection tasks. In practical implementation, pre-trained networks such as ResNet and Vision Transformer are frequently used as backbones. Bottom-layer general features are frozen, and only top-level task-specific layers are fine-tuned, which greatly lowers overfitting risks. Layer-wise unfreezing and differentiated learning rates can also be adopted to enhance semantic representation [9]. To further minimize sample requirements, meta-learning methods (MAML) acquire initialization parameters enabling rapid adaptation to new categories through multi-task training. Metric-learning approaches adopt prototypical networks or Siamese networks to directly compare sample similarities in embedding space and perform few-shot classification without re-training classifiers [10]. In addition, physical models describing ultrasonic propagation or X-ray attenuation can generate high-fidelity virtual defect samples to construct digital-twin datasets. Joint training with a small number of real samples

effectively bridges distribution gaps between simulation and reality and improves transfer robustness.

3.2. Precise defect-grading and automatic-classification strategy via multi-modal fusion

Restricted by physical principles, a single NDT modality can only reflect partial features of defects and can hardly comprehensively evaluate three-dimensional morphologies, hidden positions, and hazard levels of defects. Multi-modal fusion strategies integrate information from multi-source sensors, including ultrasonic, radiographic, visual, and infrared sensors, so as to realize comprehensive characterization and accurate grading of defects. At the data level, registered radiographic images and infrared thermograms are channel-stacked to obtain multi-spectral inputs [11]. At the feature level, independent feature-extraction branches are built for each modality. Cross-attention or adaptive gating dynamically amplifies complementary information among modalities and suppresses redundant or contradictory information. For fatigue cracks, ultrasonic B-scans provide burial depths and internal orientations, while optical imaging reveals surface opening conditions. Networks after gating fusion can accurately infer crack depth and size, and automatically judge whether a defect is a tiny surface crack, a shallow crack, or a hazardous through-thickness crack. At the decision level, Bayesian ensemble or Dempster-Shafer evidence theory fuses probabilities predicted by each modality, which effectively addresses unreliable classification results caused by modality absence or confidence conflicts [12].

3.3. Defect quantitative-assessment strategy assisted by explainable artificial intelligence

In safety-critical fields, testing results shall feature transparency and quantitative grounds, so black-box models lacking interpretability cannot be adopted. Explainable artificial intelligence endows intelligent recognition with sufficient auditability by visualizing model decision grounds. Techniques such as Grad-CAM and integrated-gradient methods generate high-resolution heat-maps marking image regions to which models pay attention during defect discrimination. If highlighted regions are consistent with real defect morphologies verified by metallographic examinations, it is confirmed that the model focuses on physically valid features. Otherwise, the system automatically triggers manual review to prevent misjudgment caused by spurious background correlation. On the basis of precise localization, attention-guided segmentation networks (Mask R-CNN or fine-tuned variants of the Segment Anything Model (SAM)) yield pixel-level defect contours and automatically compute quantitative parameters such as length, area, and aspect ratio. These parameters can be automatically compared against acceptance criteria to produce inspection reports with quantitative conclusions [13]. Moreover, Monte-Carlo Dropout or deep ensembles are utilized for uncertainty quantification, supplying confidence intervals for every assessment, for example, defect area: 3.52 ± 0.31 mm² (95 % confidence level), so as to avoid erroneous judgments stemming from over-confidence [14]. For one-dimensional signals such as ultrasonic A-scan waveforms, temporal attention highlights defect-echo intervals. Combined with sound-velocity data, it enables precise quantification of defect depth and equivalent size.

3.4. Joint strategy of online continual learning and predictive health management

During long-term service of industrial components, defect patterns and background noise change along with operating conditions, so offline models with fixed parameters gradually degrade in performance. Online-continual-learning strategies enable edge-deployed models to keep evolving from streaming testing data without full retraining. To mitigate catastrophic forgetting, elastic weight consolidation is adopted to preserve prior knowledge. Memory replay replays a small proportion of representative old

samples during update training to maintain cross-stage feature stability. Meanwhile, federated-learning frameworks allow multiple devices to collaboratively update global models without sharing raw data, thus protecting data privacy and fully exploiting distributed operational data. Furthermore, intelligent-recognition outputs are connected to predictive-health-management systems. Transformers or long short-term memory networks conduct spatio-temporal modeling for historical testing sequences to capture evolution trends of parameters such as crack length and depth. Physical constraints such as the Paris law can be embedded to estimate remaining service life when cracks expand to critical dimensions [15]. Accordingly, the system adjusts testing intervals and maintenance timelines according to practical conditions, accomplishing the shift from "defect detection" to "forecasting defect evolution".

4. Conclusion

Artificial-intelligence-enhanced non-destructive-testing technology has evolved from an auxiliary tool into a core module for autonomous decision-making. This paper systematically sorts out optimization approaches including multi-source-data augmentation and cleaning, model lightweighting with edge acceleration, hybrid physical-and-data-driven imaging optimization, and end-to-end workflow reconstruction, which effectively resolve efficiency- and robustness-related drawbacks of conventional testing. On this basis, it proposes intelligent-recognition methods: deep-transfer-learning-based few-shot recognition, multi-modal-fusion-enabled grading, explainability-assisted quantitative assessment, and the joint framework of online continual learning and health management. These approaches realize the leap from raw-signal input to precise interpretation and quantitative decision-making. Optimization paths supply high-quality inputs and energy-efficient carriers for recognition, while intelligent recognition drives optimization iteration via requirement feedback. The two lines integrate and advance in coordination. Future research shall further investigate self-adaptation under complex working conditions, model-safety certification, human-machine hybrid augmented intelligence, and other topics. These efforts will promote non-destructive testing toward fully autonomous, explainable, and evolvable unmanned intelligent inspection, and guarantee structural safety for high-end equipment throughout their whole life-cycle.

Disclosure statement

The author declares no conflict of interest.

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