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Intelligent detection of thermal damage and mechanical failure in polycrystalline diamond compact bits for deep high-temperature geothermal drilling

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Abstract

In deep geothermal resource development, the combination of high temperatures and highly abrasive hard-rock formations causes frequent thermal damage and mechanical failure of polycrystalline diamond compact (PDC) bits, severely limiting drilling efficiency and cost-effectiveness. Traditional manual grading methods struggle to identify subtle early-stage thermal damage under harsh field conditions. To address this challenge, this paper proposes DABD-Net, a deep learning network specifically designed for intelligent damage recognition of PDC bits in geothermal drilling environments. Tailored to the subtle thermal damage and complex corrosive-abrasive wear patterns characteristic of geothermal drilling, the model incorporates a Dynamic Fusion Residual Network (DFRNet) to improve the capture of microscopic thermal damage textures. A dedicated image dataset comprising seven typical damage types was also constructed. The backbone of DABD-Net is an optimized DFRNet designed specifically for extracting damage features from PDC bits. This hybrid architecture efficiently captures local and directional features using PCAConv and EMA modules, while a Transformer module models long-range

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contextual relationships. In the neck, a Dual-Path Aggregation Module (DPAM) is introduced to enhance multi-scale feature localization by effectively integrating high-level semantic information with low-level spatial details. Experimental results show that DABD-Net achieves significantly higher average precision and precision rates on the test set compared with RT-DETR and YOLO-series models. In particular, for thermal damage (the most critical and difficult-to-detect failure mode in geothermal drilling), the proposed model improves detection precision by approximately 150% over baseline models. Recognition accuracy for corrosion-abrasion damage induced by geothermal fluids also improved significantly. The proposed method enables end-to-end high-precision detection under complex lighting and background conditions at the field site after tripping out, providing an intelligent tool for post-trip bit assessment and bit-retirement decisions in geothermal drilling.

Keywords: Deep geothermal drilling; PDC bit failure; Object detection; Deep learning

1 Introduction

Geothermal energy is a clean and stable renewable resource. Its development is increasingly targeting deeper, hotter, and geologically more complex hot dry rock formations. However, deep geothermal drilling encounters extreme downhole conditions, requiring polycrystalline diamond compact (PDC) bits to cut highly abrasive granitic or metamorphic formations for extended periods (Capik and Yilmaz, 2021). These conditions cause rapid frictional heat buildup in the bit, leading to thermal cracking and accelerated wear. This has become a primary factor limiting drilling efficiency and increasing non-productive time in geothermal operations. Timely and accurate assessment of bit damage after tripping out is essential for characterizing downhole lithology, optimizing subsequent drilling parameters, and preventing catastrophic downhole accidents caused by bit disintegration (Tian et al., 2022; Ma et al., 2024). Consequently, rapid and reliable bit damage detection and failure analysis are not only fundamental to ensuring efficiency and safety in deep geothermal but also critical for advancing deep drilling toward intelligent and automated operations. Such capabilities are vital for parameter optimization, remaining useful life prediction, and prevention of safety incidents caused by bit failure (Cirimello et al., 2018; Katiyar et al., 2021; Shan et al., 2026).

Current drill bit damage assessments rely heavily on manual inspections by on-site personnel. This approach, however, has significant limitations. It is time-consuming, costly, and heavily dependent on the expertise and subjective judgment of inspectors, resulting in poor consistency and reliability of assessments. Moreover, current manual inspections generally follow the International Association of Drilling Contractors (IADC) dull grading system, which was developed primarily for conventional oil and gas drilling. This standard inadequately describes the microscopic thermal fatigue cracks and high-temperature erosion commonly observed in geothermal wells. It therefore exhibits clear limitations in characterizing the complex damage patterns encountered in geothermal resource extraction. As a result, it fails to meet the demands of modern drilling for fine-grained and automated analysis and cannot support integration with emerging intelligent drilling systems (Alam et al., 2022; Winters and Doiron, 1987).

To address the limitations of manual inspections, automated detection methods for drill bit damage have emerged along two main paths. The first is real-time while-drilling monitoring, which primarily analyzes signal data during drilling, such as vibration, acoustic waves, and motor current, to indirectly infer bit condition (Rafezi and Hassani, 2021; Tran et al., 2022). While somewhat effective, these methods are sensitive to complex subsurface conditions and require extensive equipment knowledge and signal processing expertise, limiting their adaptability (Senjoba et al., 2024). The second is post-trip visual assessment, which involves direct surface damage inspection of the retrieved drill bit. With advances in computer vision and deep learning, shows greater promise. For instance, (Ashok et al., 2020) used the YOLOv3 model with traditional image processing to automatically identify cutting teeth and quantify damage areas in 2D images. (Wei et al., 2025) developed a YOLOv7-based model for intelligent recognition of various damage types in PDC drill bits. Similarly, (Ali et al., 2023) employed YOLOv5 to simultaneously detect and classify multiple damage types in a single step, streamlining the process. Subsequent research has tackled more complex tasks by adopting multi-stage and task-decoupled strategies. For example, (Chu et al., 2022) developed a comprehensive detection framework that first distinguishes between top and side views of drill bits, then performs tasks like cutting teeth localization, damage quantification, and region segmentation, ultimately generating automated IADC-compliant reports. (Yang et al., 2025) proposed a decoupled strategy using YOLOv10 to locate cutting teeth, followed by two separate networks for assessing wear levels and classifying damage types.

Although image-based detection techniques show considerable promise, their application in geothermal drilling faces substantial challenges. Previous research has largely relied on general-purpose object detection models (Ali et al., 2023) or multi-model decoupled architectures that first locate and then classify damage (Chu et al., 2022; Yang et al., 2025). While these approaches achieve some degree of damage identification, they increase system complexity and hinder fast, integrated detection; moreover, their damage taxonomies are largely oriented toward conventional oil-and-gas drilling and do not include geothermal-specific failure modes such as heat cracking. They also often struggle to simultaneously maintain sensitivity to tiny defects and an understanding of overall bit morphology when handling the wide scale range from large-area mechanical fractures to subtle thermal damage in geothermal drill bits. In addition, retrieved drill bits from the field frequently carry residues of drilling fluid and rock cuttings. Combined with variable lighting and inconsistent shooting angles (Pastusek et al., 2018; Watson et al., 2022), these factors cause general models to lack robustness under complex background interference and exhibit very limited capability in extracting and distinguishing features of subtle damage. In contrast to previous studies, the key improvement of this research lies in the proposal of a Dynamic Adaptive Drill Bit Damage Detection Network (DABD-Net) specifically designed for the complex conditions of geothermal drilling. Built upon the RT-DETR framework, DABD-Net integrates and adapts established design components, including multi-scale attention, partial convolution, and multi-scale feature aggregation, and optimizes their integration for the characteristics of geothermal PDC-bit damage. This network adopts an end-to-end integrated architecture, aiming to achieve high-precision automatic recognition of multi-scale thermo-mechanical composite damage under the challenging background conditions of geothermal drilling sites.

This study constructed a drill bit damage image dataset that includes images collected after both conventional and geothermal drilling operations. The dataset covers seven key damage types ranging from conventional mechanical wear to high-temperature thermal cracks unique to geothermal conditions, providing a foundation for intelligent detection research in the geothermal field. Building on this dataset, this study propose the DABD-Net detection model. Its core components are a Dynamic Fusion Residual Network (DFRNet) backbone tailored for capturing microscopic thermal fatigue textures and a Dual-Path Aggregation Module (DPAM) neck designed to enhance multi-scale feature localization. This integrated architecture effectively extracts diverse features ranging from subtle thermal cracks to

extensive wear regions. Experimental results demonstrate that DABD-Net substantially outperforms both the RT-DETR baseline and all YOLO-series models across key metrics on the geothermal mixed dataset. Of greatest engineering significance, the model achieves a dramatic performance improvement in detecting thermal damage, the most critical and challenging failure mode in geothermal drilling. This work not only delivers an efficient bit-condition perception tool for automated assessment in deep geothermal drilling but also offers new insights and validated approaches for addressing similar complex surface-defect detection problems in extreme manufacturing environments.

The remainder of the paper is organized as follows: Section 2 describes the dataset construction, Section 3 details the DABD-Net architecture and its core modules, Section 4 presents comparative experiments, ablation studies, and multi-scenario detection results, and Section 5 summarizes the study’s conclusions.

2 Experimental materials

2.1 Dataset

PDC bit failure represents a critical challenge in deep geothermal energy development, resulting from the combined effects of high-temperature hard-rock environments, high-frequency mechanical impacts, and corrosive geothermal fluids. To ensure the model can learn broad features while precisely capturing damage patterns unique to geothermal drilling, this study constructed a multi-source PDC drill bit damage image dataset. The development data (training and validation sets) come from two sources. One source consists of 313 drill bit damage images extracted from End-of-Well Reports of multiple geothermal wells at the U.S. Department of Energy’s Utah FORGE test site (McLennan, 2023; Winkler, 2021). These images feature highly representative high-temperature thermal cracks and hard-rock wear characteristics, providing a strong basis for evaluating the model’s generalization capability under extreme geothermal conditions. The other source comprises 1,168 images from publicly available Roboflow datasets of PDC drill bits from conventional oil and gas drilling, which supplies diverse mechanical damage samples. Initial images were screened to select those with clear and typical damage features. Damage regions were then analyzed, labeled, and annotated with bounding boxes on the

Roboflow platform. All images were standardized to a resolution of 640×640 pixels. To prevent data leakage, a group-based splitting strategy was adopted: geothermal images were grouped by bit serial number, and Roboflow images by original image ID, ensuring that all views of the same bit or original image appear in only one subset. The development data comprise 7,251 annotated instances, divided into a training set of 5,727 instances and a validation set of 1,524 instances. In addition, for an independent and unbiased final evaluation, a separate test set of 278 images containing 981 annotated instances, fully independent of and non-overlapping with the above data, was assembled, comprising 62 images from Utah FORGE geothermal wells and 216 images from the Roboflow projects. The geothermal test images were additionally collected and annotated, whereas the Roboflow test images were withheld at the group level from the same projects. This test set was fixed and annotated after the development set had been finalised and before any training run reported in this study was initiated, and it was held out throughout model development. Its group identifiers were cross-checked against those of the training and validation sets and confirmed to be mutually disjoint, so that no view of the same bit or the same original image appears in more than one subset. During training, the validation set is used only for weight selection and hyperparameter tuning, while the test set is kept strictly isolated throughout training and tuning and is used only once, to report all quantitative results of this study; no test image was selected, excluded, or re-annotated on the basis of model output.

PDC drill bits frequently experience premature failure during drilling in hard and heterogeneous geothermal reservoirs due to dynamic impact. The primary failure modes include impact damage, wear, thermal damage, and corrosion (Li and Song, 2002; Shao et al., 2025). Despite their excellent wear resistance, PDC cutters are highly susceptible to brittle fracture under the combined effects of elevated bottom-hole temperatures and hard-rock impacts (Petrović et al., 2011). Dynamic impact damage in geothermal hard-rock drilling is classified into tangential and axial directions. Axial impact acts perpendicular to the PDC cutter, whereas tangential impact opposes the cutter's direction of motion and is primarily induced by bit torsion and vibration (Witt-Doerring et al., 2021). In addition, at very high rotational speeds, PDC cutters easily trigger the bit whirl effect. This causes the cutters to experience reverse and lateral abnormal acceleration together with high-intensity impact loads, resulting in severe chipping and accelerated wear (Brett et al., 1989; Coudert et al., 2020). Such severe damage manifests as ultimate fracturing, in which cracks destroy not only the diamond layer but also propagate deeply into

the tungsten carbide substrate, leading to substantial loss of cutting material (K. Abbas, 2018). Once the cutters fail, the unprotected bit matrix becomes directly exposed to the harsh environment. This exposure triggers extensive matrix erosion and additional damage, ultimately resulting in complete failure of the PDC drill bit. Thermal damage is the most critical failure mode in geothermal drilling. Intense frictional heat from highly abrasive formations, combined with elevated formation temperatures, causes rapid bit temperature rise. Differential thermal expansion between the polycrystalline diamond layer and the tungsten carbide substrate generates substantial thermal stress, inducing microscopic thermal cracks (Ortega and Glowka, 1984; Petrović et al., 2011). Corrosive elements in drilling fluids and corrosive formation environments further degrade the drill bit, limiting its service life (Kembaiyan and Keshavan, 1995; Zavareh et al., 2016). Deep geothermal reservoirs contain H_2 , CO_2 , and high-salinity fluids that can increase corrosion rates by 4-10 times compared with conventional conditions (Straume et al., 2021; Tuttle et al., 2020). Moreover, geochemical reactions between CO_2 and the reservoir fluids and rocks further acidify the downhole environment, thereby intensifying corrosion (Lu et al., 2025). In such extreme environments, corrosive fluids and high-velocity drilling fluid produce a strong erosion-corrosion synergistic effect. This continuously strips the protective surface layer, accelerates substrate degradation and material loss, and ultimately appears visually as typical corrosion-wear features (Kembaiyan and Keshavan, 1995). In addition, the complex and variable geological conditions in geothermal drilling further intensify the complexity of bit wear (Chen et al., 2026; Kalhori et al., 2024).

Based on these damage analysis criteria, seven key damage modes significantly affecting drilling performance and safety were identified. Accordingly, the dataset samples are classified into seven categories based on their formation mechanisms and morphological characteristics: BHA Whirl Damage (BWD), Corrosion Wear (CW), Gauge Damage (GD), Heat Checking (HC), Matrix Damage (MD), PDC Cutter Surface Impact Damage (SD), and PDC Cutter Tip Impact Damage (TD), as shown in Fig. 1.



Fig. 1 Representative samples of the seven damage categories in the drill bit damage dataset.

The dataset exhibits class imbalance, which reflects the varying occurrence frequencies of different

damage modes in real-world engineering practice. For example, SD is the most frequent category, with 2,675 instances, whereas HC, the rarest category, has only 70 instances. This distribution realistically mirrors the difficulty of detecting thermal damage at an early stage by visual inspection in geothermal field conditions, and presents practical challenges for training robust models capable of capturing small-sample, low-contrast thermal damage features. Table 1 reports the number of annotated instances in each of the seven categories for the training, validation, and independent test sets. The three splits share the same long-tailed composition, with SD the most frequent and HC the rarest category. Damage regions were annotated with bounding boxes on the Roboflow platform according to a labeling guide established before annotation began. The seven categories were defined by their formation mechanisms and morphological characteristics, with explicit rules for the two pairs that are visually most similar: SD and TD were distinguished by the location of the damage centre on the cutter, damage on the cutter face being annotated as SD and damage at the cutter tip as TD; HC and CW were distinguished by whether material loss accompanies the damage, a fine reticular crack network without appreciable material loss being annotated as HC, and discolouration accompanied by substrate thinning as CW. Three further conventions were applied consistently: regions smaller than 10 x 10 pixels were not annotated; damage of the same category in contact on a single cutter was merged into one box, while damage on different cutters was annotated separately; and regions that were occluded or out of focus to the extent that the damage type could not be determined were left unannotated. Annotation was carried out by two engineers with a drilling engineering background, who received common training based on the IADC dull grading system and the category definitions used in this study, and all annotations were subsequently reviewed image by image against the guide.

Table 1. Distribution of annotated instances across the data splits

Category	Training set	Validation set	Test set	Total
BWD	857	186	145	1188
CW	235	70	43	348
GD	373	104	69	546
HC	42	16	12	70
MD	775	229	165	1169
SD	1843	542	290	2675
TD	1602	377	257	2236

2.2 Data augmentation

To ensure accurate detection of diverse and often similar visual features in drill bit damage, such as the fine, web-like cracks of HC or subtle differences between fracture types, this study developed a comprehensive data augmentation strategy tailored to these characteristics. Given the scarcity of HC in the dataset and its delicate crack patterns, which are easily obscured by complex backgrounds, Mosaic augmentation was employed. This technique combines four images to create varied training scenarios, requiring the model to locate small crack networks in challenging contexts, significantly enhancing small-target detection (Yang et al., 2022). Additionally, to improve differentiation between similar damage types like SD and TD, Mixup augmentation was introduced, generating virtual samples at class boundaries to promote robust feature learning and reduce confusion between fracture types (Zhang et al., 2017).

To address features like the spiral scratches of BWD and the directional patterns of TD, this study used geometric transformations, including random horizontal flips, ensuring the model's detection is unaffected by the drill bit's orientation during imaging. To simulate on-site lighting variations and the impact of oil stains or rust on color- and texture-related defects like CW, we applied optical distortions, randomly adjusting image hue, saturation, and brightness. The effects of these augmentations are shown in Fig. 2. Data augmentation was applied exclusively to the training set after dataset splitting; the validation set retained the original, unaugmented images. The above data augmentation strategies are particularly important for the underrepresented HC category, which is the rarest class in the dataset and objectively reflects the difficulty of collecting early-stage thermal failure samples from geothermal drilling sites. Through Mosaic multi-image stitching, Mixup virtual sample generation near class boundaries, and HSV photometric perturbations, the model is exposed to a much larger number of effective HC feature observations per epoch than the original sample count. This enables the model to learn the visual semantics of HC rather than memorizing pixels from specific images.

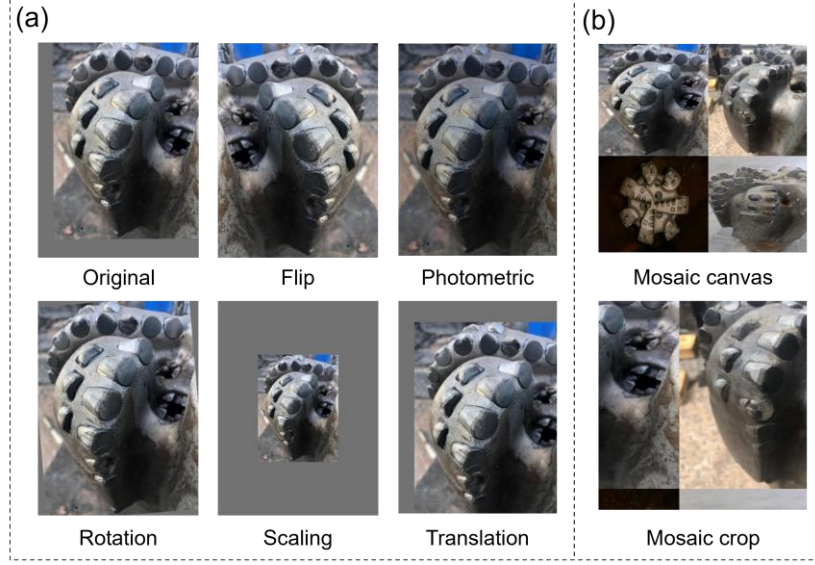


Fig. 2 Data augmentation effects (a) Geometric and optical transformations (b) Mosaic augmentation.

3 Methods

To achieve fast and accurate detection of the complex and diverse damage features exhibited by PDC bits, this paper proposes DABD-Net. The core innovation lies in a custom-designed backbone, termed Dynamic Fusion Residual Network (DFRNet), optimized specifically for drill-bit image feature extraction, and a Dual-Path Aggregation Module (DPAM) neck that significantly improves multi-scale feature localization. Rather than relying on dynamic routing that changes the computation path with the input, DABD-Net keeps a fixed network structure and applies input-adaptive weighting to a subset of channels via PCAConv. This eliminates gradient-divergence risks and substantially reduces computational overhead, while still adaptively increasing attention to subtle thermal-damage textures. This section details the overall architecture of DABD-Net and the design principles and implementation of its core components.

3.1 Overall architecture

The model's framework is illustrated in Fig. 3. Built on the high-performance, real-time, end-to-end Real-Time Detection Transformer (RT-DETR) (Zhao et al., 2024), the original backbone is replaced with DFRNet, specifically designed to efficiently extract critical visual features of drill bit damage. Multi-

scale feature maps from DFRNet are then processed by the DPAM neck. Through its unique bidirectional path aggregation structure, DPAM deeply integrates backbone features, producing outputs that combine rich semantic information with high-resolution spatial details. The RT-DETR detection head leverages these high-quality fused features, using an IoU-aware query selection mechanism and Transformer decoder to directly predict the precise locations and categories of damage regions.

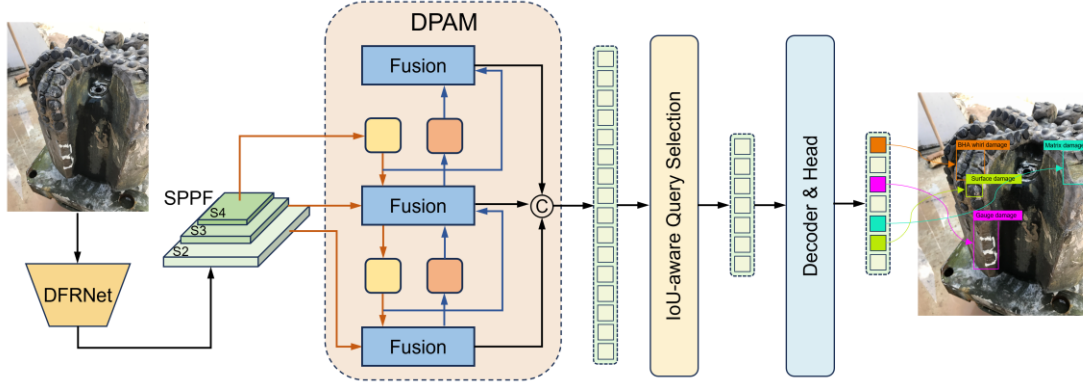


Fig. 3 Model architecture overview

3.2 Feature extraction network

To efficiently extract features from drill bit damage, which ranges from subtle thermal cracks to large surface damage against a uniform background, the DFRNet was developed as the model's backbone. This network employs a hybrid architecture, using Dynamic Fusion Residual (DFR) modules in shallow layers to capture local texture details effectively and Transformer modules in deeper layers to model global contextual relationships, as shown in Fig. 4.

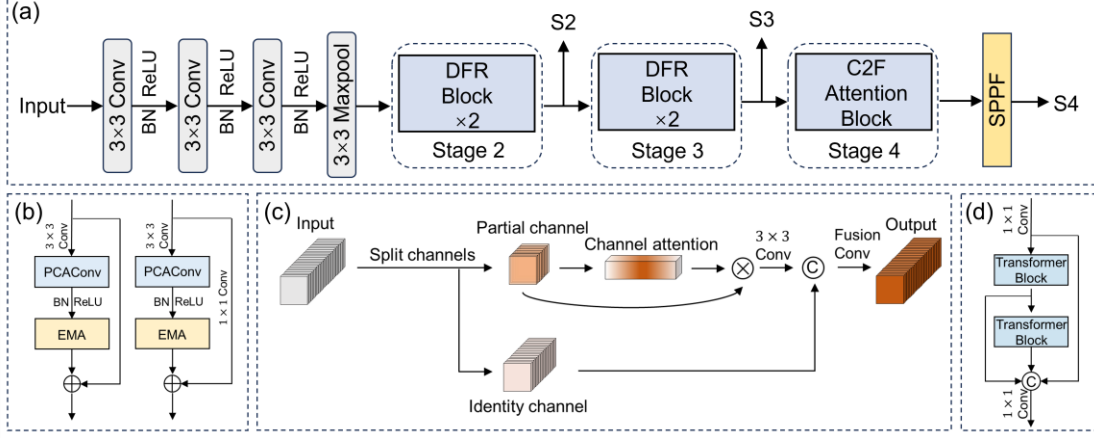


Fig. 4 DFRNet backbone structure (a) Overall DFRNet architecture, (b) DFR module, (c) PCAConv module, (d) C2fAttention module.

3.2.1 DFR module

The primary component of DFRNet is the DFR module, designed in this study. The main path of this module consists of a standard convolution, a Partial Channel Attention Convolution (PCAConv) module, and an Efficient Multi-scale Attention (EMA) module, connected in series with a residual connection, as shown in Fig. 4(b) (He et al., 2016). The core of the main path is the PCAConv operator (Huang et al., 2025), built on Partial Convolution (PConv), a convolution paradigm that reduces computational redundancy and memory access by processing only a subset of input feature map channels, thereby improving network efficiency (Chen et al., 2023). However, PConv’s static operation treats all selected channels equally, lacking adaptability to input content. To address this limitation, a channel attention mechanism was incorporated, forming PCAConv.

The workflow of PCAConv is illustrated in Fig. 4(c). For a given input feature map ($F \in \mathbb{R}^{C \times H \times W}$), the channel dimension is split into two parts: ($F \in \mathbb{R}^{C \times H \times W}$), which undergoes convolution, and ($F \in \mathbb{R}^{C \times H \times W}$), which remains unchanged. Unlike PConv, before convolution, a computationally efficient channel attention function (f_{ca}) first generates a dynamic channel weight vector (w) for F_p . This process is expressed as:

$$w = \sigma(f_{ca}(F_p)) \quad (1)$$

where f_{ca} is implemented by global average pooling (GAP) and two 1×1 convolution layers, and σ

denotes the Sigmoid activation function.

The generated weight vector ($w \in \mathbb{R}^{C_p \times 1 \times 1}$) is applied to F_p via channel-wise multiplication, producing a weighted feature map (F'_p), as shown in:

$$F'_p = F_p \otimes w \quad (2)$$

F'_p is then processed by a standard 3×3 convolution layer (f_{conv}) for spatial feature extraction. The result is concatenated with the unchanged F_{id} along the channel dimension and passed through a 1×1 convolution f_{fus} for cross-channel information fusion, yielding the final output (Y), as expressed in:

$$Y = f_{fus}(\text{Concat}(f_{conv}(F'_p), F_{id})) \quad (3)$$

PCACConv was developed to address the severe feature imbalance typical of geothermal bit damage. For instance, HC manifests as extremely fine reticular textures on the cutter surface that are easily overwhelmed by background noise. By applying adaptive channel weighting, PCACConv markedly enhances the response to these low-contrast thermal textures.

After PCACConv captures weighted local features, an EMA module is incorporated in series (Ouyang et al., 2023). The purpose of introducing EMA is to effectively capture long-range spatial dependencies within the feature map without substantially increasing computational cost. This capability is critical for accurately identifying directional and extended drill bit damage features.

The EMA module addresses the limited receptive field of traditional convolutions through cross-spatial learning. The input feature map is first divided into multiple groups along the channel dimension to reduce computational complexity. Then, in two parallel branches, 1D global average pooling is applied to the grouped feature maps, with one branch along the height dimension and the other along the width dimension, encoding global information in both spatial directions. These feature descriptors, capturing different spatial dimensions, are concatenated and processed by a 1×1 convolution to explicitly model interactions and dependencies between height and width dimensions. This cross-spatial learning generates two independent attention weight vectors, corresponding to the height and width dimensions of the feature map. These vectors are sequentially applied to the original grouped feature maps, adaptively recalibrating feature responses in both spatial directions. This process is described as:

$$Y = A_w \cdot (A_h \cdot X') \quad (4)$$

where X' is the grouped input feature, A_h and A_w are the height and width attention maps obtained through cross-spatial learning.

The cross-space learning mechanism introduced by the EMA module is particularly valuable for analyzing compound wear in geothermal drilling. For BWD, which typically appears as irregular helical scratches, EMA effectively captures these multidimensional morphological patterns. Similarly, crack propagation direction is a critical discriminant for TD. The long-range spatial dependency modeling capability of EMA enables the model to track and recognize such patterns with greater accuracy.

3.2.2 *C2fAttention block*

The DFRNet architecture comprises a Stem layer and three feature extraction stages. Stages 2 and 3 consist of stacked DFR modules for efficient local feature extraction. In the deeper stages, a Transformer Block is incorporated for global context modeling (Dosovitskiy et al., 2020). Deep networks require a global perspective to understand damage attributes, such as distinguishing large-scale BWD from GD at the gauge, which demands both local texture recognition and awareness of damage position relative to the drill bit's contour. Accordingly, the C2fAttention Block, shown in Figure 4(d), is designed with an internal self-attention mechanism to effectively establish long-range dependencies, providing a global context perspective and addressing the limitations of traditional convolutions in global perception. This hybrid convolution-Transformer design enables DFRNet to balance precise local detail capture with accurate global relationship understanding.

3.2.3 *SPPF module*

Following the DFRNet backbone, a Spatial Pyramid Pooling-Fast (SPPF) module is integrated to enhance robustness to varying target scales without significantly increasing computational cost. The wide range of drill bit damage sizes poses significant challenges to feature representation. The SPPF module draws inspiration from the Spatial Pyramid Pooling (SPP) structure (He et al., 2015). Traditional SPP modules use parallel max-pooling layers of different sizes to capture multi-scale contextual information, but large-kernel pooling introduces computational overhead. The SPPF module achieves similar results through an efficient serial structure (Jocher et al., 2020). In the model, the SPPF module takes the deepest

DFRNet features as input, processes them through three sequential max-pooling layers, and concatenates the outputs with the original input feature map along the channel dimension, followed by a convolution layer for information fusion. This output, S4, contains rich multi-scale contextual information, significantly improving the model's ability to detect damages of varying sizes.

3.3 DPAM neck network

To precisely locate damage boundaries, especially for damages like MD occurring at material interfaces, effective fusion of high-level semantic information and low-level detailed information is essential. To this end, the Dual-Path Aggregation Module (DPAM) neck network is designed as a bidirectional path aggregation network, as shown in Fig. 5(a). DPAM incorporates two information fusion paths: a top-down path and a bottom-up path. The top-down path transfers rich semantic information from deep backbone feature maps to higher-resolution shallow feature maps through upsampling and fusion operations. After completing the top-down path, a bottom-up path is constructed, where shallow feature maps with strong localization information are downsampled and fused again with deep feature maps, supplementing precise spatial details to the semantic features (Liu et al., 2018).

Each fusion node in DPAM receives two feature maps from different levels, adjusts them individually through a 3×3 convolution, concatenates the results along the channel dimension, and performs deep fusion with another 3×3 convolution, as shown in Fig. 5(b). Through this bidirectional feature flow and fusion, DPAM produces features that combine accurate semantic information and fine spatial details, providing high-quality input for the subsequent detection head.

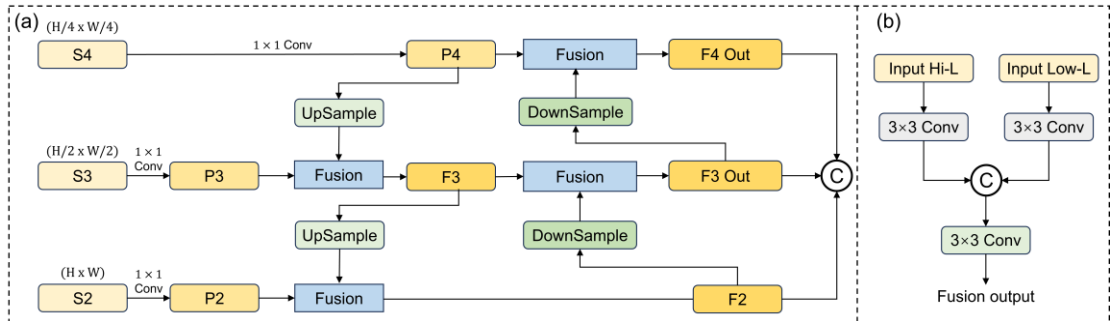


Fig. 5 DPAM neck network architecture: (a) Overall structure, (b) Fusion module.

3.4 Detection head

In the final prediction stage, the high-performance real-time detection framework RT-DETR’s head design is retained to leverage its combined advantages in accuracy, speed, and ease of deployment (Zhao et al., 2024). The detection head comprises an IoU-aware Query Selection mechanism and a Transformer decoder. Unlike traditional DETR models that use fixed, content-agnostic object queries (Carion et al., 2020), the IoU-aware Query Selection mechanism dynamically selects initial queries most likely to contain targets from numerous image locations, based on encoder features output by the DPAM module. This design significantly reduces the computational load for the subsequent decoder, critical for achieving real-time performance. Selected queries are then fed into the Transformer decoder, which optimizes them iteratively through stacked attention modules. In each layer, self-attention enables information interaction among queries to eliminate redundant predictions, while cross-attention extracts the most relevant visual features from DPAM’s multi-scale feature maps. Through multiple iterations, each query’s category and location information is progressively refined.

A key advantage of the RT-DETR detection head is its end-to-end nature. By producing a sparse, non-redundant set of predictions, the need for traditional non-maximum suppression post-processing is eliminated. This simplifies the detection pipeline and enables joint optimization of all model components. Consequently, the adoption of the RT-DETR detection head equips DABD-Net with a robust, efficient, and streamlined prediction backend, well-suited for drill bit damage detection tasks requiring rapid deployment and high-precision analysis.

4 Results and discussion

4.1 Training environment

Details of the experimental setup are presented in Table 2. The hardware configuration includes a server equipped with a 14-core Intel(R) Xeon(R) Gold 6330 CPU, 60GB of memory, and an NVIDIA GeForce RTX 3090 (24GB) GPU. The software environment is built on Python 3.12 and the PyTorch 2.8.0 deep learning framework, with CUDA 12.8 utilized for accelerated computing. Model training

employs the AdamW optimizer with a weight decay coefficient of 0.0005. All input images are resized to 640×640 pixels, with a batch size of 28. Training is conducted with an initial learning rate of 0.0001 over 150 epochs. No early stopping mechanism was applied; the model completed all 150 epochs. Model weights were selected according to the best historical performance on the validation set during training (specifically, the epoch with the highest validation mAP0.5-0.95, rather than the final-epoch weights), and the selected model was then evaluated only once on an independent test set that took no part in training or tuning. All quantitative results reported in this study come from this test set, thereby avoiding the optimistic bias that could arise from reporting on the validation set used for tuning.

Table 2. Experimental environment

Parameter	Set up
CPU	14 vCPU Intel(R) Xeon(R) Gold 6330 CPU @ 2.00 GHz
GPU	NVIDIA GeForce RTX 3090 (24GB)
RAM	60GB
Integrated development environment	Python 3.12 PyTorch 2.8.0 CUDA 12.8
Operating system	Ubuntu 22.04

4.2 Model training

Fig. 6 and Fig. 7 show the performance metrics and loss curves of DABD-Net over 150 training epochs, respectively, illustrating the training process of the model. As shown in Fig. 6 and Fig. 7, all performance metrics exhibit a steady increase and eventual convergence. The precision curve shows minor fluctuations early in training, followed by a rapid rise, stabilizing after 60 epochs and converging to a high level. The recall and mAP curves demonstrate smoother growth, rising consistently from the start and leveling off around 100 epochs, indicating robust and stable optimization of the model’s detection and localization accuracy. Fig. 6 reports metrics computed on the training set and is presented to characterise the fitting process; all performance reported in this study is computed on the independent test set. Although the headline metrics plateau after roughly 100 epochs, the full 150-epoch schedule was retained because categories with few samples, such as HC, require more iterations to learn their subtle texture features, and premature termination could leave these long-tailed categories incompletely converged.

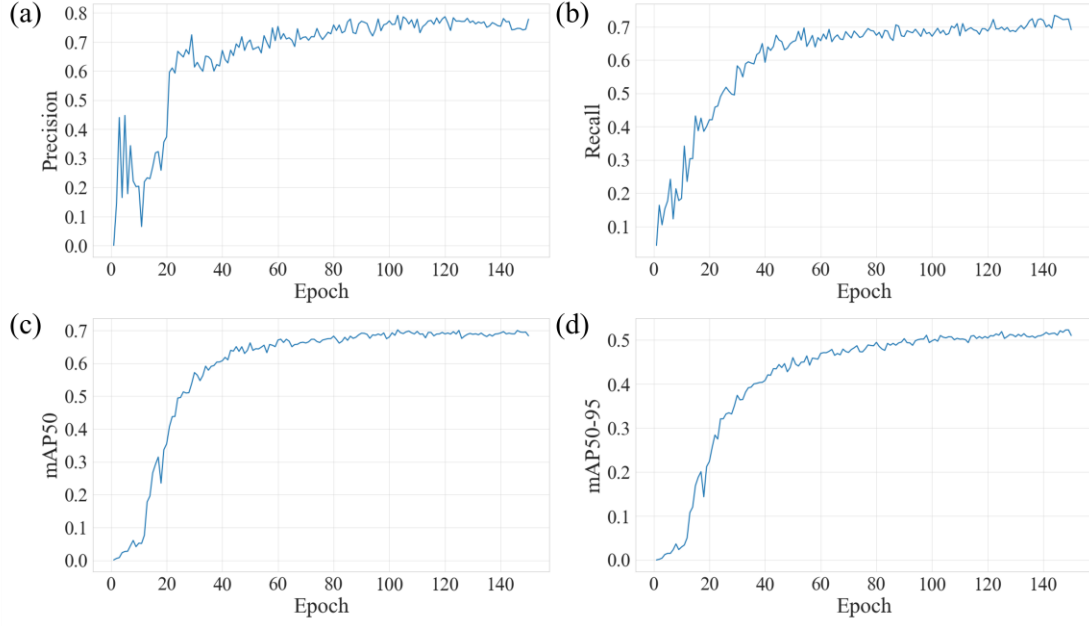


Fig. 6 DABD-Net performance metrics on the training set (a) Precision (b) Recall (c) mAP50 (d) mAP50-95.

As shown in Fig. 7, the losses on both the training and validation sets decrease rapidly in the early stages of training. In the later stages the two diverge: fitting a linear trend over epochs 120-150, the three training losses continue to decrease while the corresponding validation losses increase by 0.006, 0.029, and 0.005, indicating mild overfitting. The final-epoch weights were therefore not used; instead, the epoch with the highest validation mAP0.5-0.95 was selected and evaluated once on the independent test set, so the reported performance is not affected by this late-stage divergence.

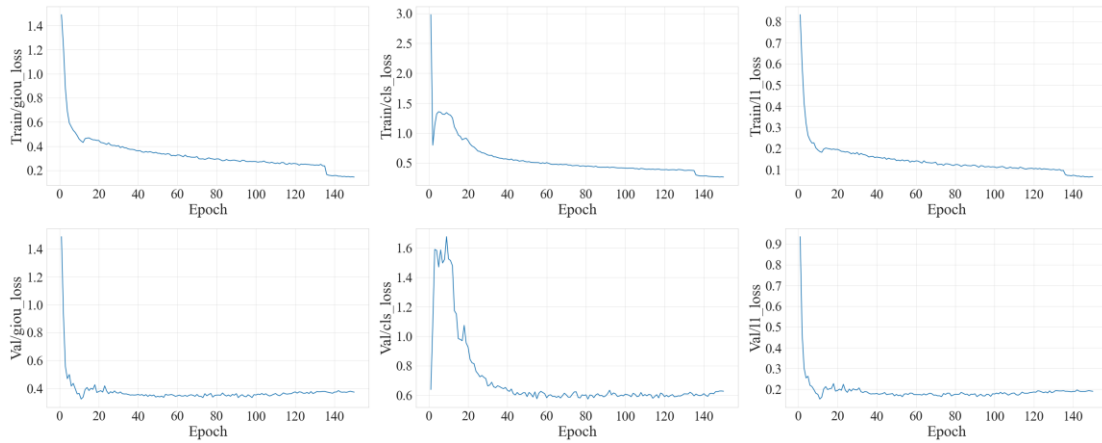


Fig. 7 DABD-Net loss function curves

As shown in Table 3, compared with the baseline RT-DETR, DABD-Net achieves higher precision on six of the seven damage categories and is essentially on par with the baseline on the GD category, demonstrating the overall effectiveness of the proposed method. For instance, DABD-Net achieves AP values of 0.832 and 0.804 for BWD and MD, respectively. Of greatest engineering significance is the breakthrough improvement in HC detection. This failure mode is the most characteristic and critical precursor to catastrophic bit failure in geothermal hard-rock drilling. Owing to its subtle and complex morphology, RT-DETR records an AP of only 0.200 for HC and suffers frequent missed detections. In contrast, DABD-Net raises the AP to 0.501. This enhancement corresponds to more sensitive identification of early thermal cracks caused by overheating. Since heat checking originates from the accumulation of frictional heat, more reliable post-trip detection of this failure mode may provide a useful reference for subsequent judgements on whether bottom-hole temperature or weight-on-bit is abnormal, and thereby help create conditions for reducing the risk of thermal collapse and associated downhole incidents. Detection AP for CW, prevalent in geothermal fluid environments, improves by 0.224. This reflects stronger discrimination of damage patterns involving colour and texture variation, and the detected extent of corrosion wear may, in combination with fluid chemistry and well data, provide a reference for inferring downhole fluid corrosivity and for casing material selection.

Table 3. Detection performance comparison on test set before and after improvements compared to baseline model

Model	AP _{BWD}	AP _{CW}	AP _{GD}	AP _{HC}	AP _{MD}	AP _{SD}	AP _{TD}
RT-DETR	0.738	0.239	0.604	0.200	0.677	0.645	0.620
DABD-Net	0.832	0.463	0.593	0.501	0.804	0.672	0.702
$\Delta\%$	$\uparrow 12.7\%$	$\uparrow 93.7\%$	$\downarrow 1.8\%$	$\uparrow 150.1\%$	$\uparrow 18.8\%$	$\uparrow 4.2\%$	$\uparrow 13.2\%$

4.3 Model comparison

To comprehensively evaluate the effectiveness of the proposed DABD-Net, a comparative experiment was conducted against a range of object detection models on a custom drill bit damage dataset. The models compared include the baseline RT-DETR and mainstream YOLO series models, namely YOLOv5, YOLOv8, YOLOv10, and YOLOv12 (Jocher, 2022; Jocher et al., 2024; Tian et al., 2025; Wang et al., 2024). All models were trained and evaluated under identical experimental conditions, with performance measured using test set metrics.

As shown in Table 4, DABD-Net achieves the best performance across all key metrics. Specifically, on the test set, DABD-Net attains an mAP_{0.5} of 0.652 and an mAP_{0.5-0.95} of 0.477, significantly outperforming all compared models. On the independent test set, the second-best model, YOLOv12, attains an mAP_{0.5} and mAP_{0.5-0.95} of 0.570 and 0.387, respectively, still lagging behind DABD-Net by 0.082 and 0.091. Although the YOLO-series models show advantages in detection speed, for example YOLOv10 reaching 100.84 FPS, their detection accuracy is poor, and this performance gap becomes even more pronounced under the stricter mAP_{0.5-0.95} metric.

Table 4. Performance metrics of compared models on test set

Model	P	R	mAP _{0.5}	mAP _{0.5-0.95}	FPS
RT-DETR	0.642	0.581	0.532	0.331	94.48
YOLOv5	0.694	0.544	0.564	0.349	91.52
YOLOv8	0.706	0.555	0.562	0.381	90.70
YOLOv10	0.672	0.561	0.562	0.385	100.84
YOLOv12	0.687	0.561	0.570	0.387	94.48
DABD-Net	0.748	0.653	0.652	0.477	87.43

As shown in Table 5, the superiority of DABD-Net is further confirmed when examining average precision across individual damage categories. Under the exact same dataset split and training protocol,

the baseline RT-DETR achieved an AP of only 0.200 for HC. The YOLOv5, YOLOv8, YOLOv10, and YOLOv12 models obtained AP values of 0.193, 0.256, 0.149, and 0.230, respectively. In contrast, DABD-Net achieved AP values of 0.501 for HC and 0.463 for CW. These results represent relative improvements of 150% and 93% over the RT-DETR baseline, respectively. This outcome not only demonstrates the advantage of DABD-Net in detecting subtle, irregular, and low-frequency damage features, but also rules out the possibility of sample memorization from a cross-model perspective. If HC patterns could be simply memorized, baseline models with comparable parameter capacities would exhibit similar performance.

Table 5. Average precision of compared models for each damage category on test set

Model	AP _{BWD}	AP _{CW}	AP _{GD}	AP _{HC}	AP _{MD}	AP _{SD}	AP _{TD}
RT-DETR	0.738	0.239	0.604	0.200	0.677	0.645	0.620
YOLOv5	0.793	0.255	0.607	0.193	0.748	0.704	0.646
YOLOv8	0.787	0.264	0.639	0.256	0.676	0.666	0.649
YOLOv10	0.797	0.307	0.633	0.149	0.718	0.673	0.653
YOLOv12	0.812	0.277	0.620	0.230	0.691	0.680	0.681
DABD-Net	0.832	0.463	0.593	0.501	0.804	0.672	0.702

In summary, to achieve high-precision detection of subtle thermal damage and complex damage patterns, DABD-Net incorporates more sophisticated feature extraction and fusion mechanisms. Although this design results in slightly lower inference speed compared with some baseline models, it remains well above the real-time detection threshold required for industrial field applications. Given the high demand for accuracy in drill bit damage detection for deep geothermal drilling, DABD-Net strikes an optimal balance between accuracy and speed, confirming its superiority as an efficient and precise solution for drill bit damage detection.

4.4 Ablation study

To evaluate the effectiveness of the proposed method, a series of ablation experiments was conducted on the drill bit damage dataset to systematically analyze the impact of each improvement. Since the purpose of the ablation experiments is to make a horizontal comparison of the relative contribution of each module, all variants were evaluated on the validation set, with both training and validation metrics reported to indicate the degree of overfitting of each variant, whereas the final

performance reported in this paper is based uniformly on the independent test set. The ablation study focuses on the baseline model and independent analyses of key design elements in the backbone and neck networks, as illustrated in Fig. 8. The standard RT-DETR model is designated as Model A. To assess the effectiveness of the DFRNet backbone and its internal components, three experiments were performed: Model B1 replaces the deep-stage C2fAttention block with a DFR block, retaining a pure DFRNet backbone; Model B2 removes the SPPF module from the final model to evaluate its necessity for enhancing multi-scale feature representation; Model B3 replaces the entire DFRNet backbone with the standard RT-DETR backbone to demonstrate the superiority of the backbone replacement scheme for drill bit damage detection. To evaluate the contribution of the DPAM module, Model C replaces the neck network of the final model with the standard RT-DETR neck, using the DFRNet backbone to clearly isolate the performance improvements from DPAM’s feature fusion.

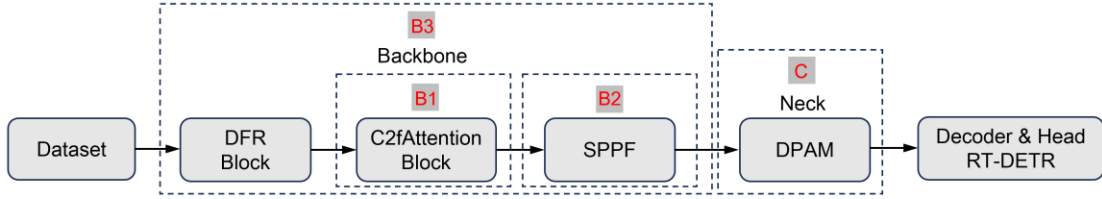


Fig. 8 Ablation study design

As presented in Table 6, all proposed modules positively impact model performance. In backbone validation, Model B3, compared to the baseline, improves mAP0.5 and mAP0.5-0.95 on the validation set by 2.0% and 3.2%, respectively, demonstrating DFRNet’s fundamental advantage in extracting drill bit damage features. Further analysis of DFRNet’s internal components shows that Model B1’s mAP0.5 and mAP0.5-0.95 decrease by 0.015 and 0.024, respectively, compared to the final DABD-Net, indicating the effectiveness of incorporating the C2fAttention block for global context modeling in deep layers. Similarly, Model B2’s performance declines relative to DABD-Net, confirming the critical role of the SPPF module in enhancing multi-scale feature representation and perception of varying damage sizes. Experiments replacing DPAM with the standard RT-DETR neck in Model C show declines in mAP0.5 and mAP0.5-0.95 by 0.028 and 0.02, respectively, strongly validating that DPAM’s unique bidirectional path aggregation structure effectively fuses high-level semantic information and low-level spatial details, significantly improving damage localization accuracy.

Table 6. Ablation study results

Model	Dataset	P	R	mAP0.5	mAP0.5-0.95
A	Train	0.742	0.648	0.616	0.428
	Validation	0.686	0.642	0.612	0.416
B1	Train	0.788	0.743	0.698	0.489
	Validation	0.743	0.679	0.634	0.439
B2	Train	0.769	0.658	0.665	0.483
	Validation	0.730	0.641	0.623	0.442
B3	Train	0.743	0.668	0.674	0.491
	Validation	0.706	0.632	0.632	0.448
C	Train	0.755	0.698	0.675	0.498
	Validation	0.738	0.634	0.621	0.443
DABD-Net	Train	0.793	0.716	0.689	0.506
	Validation	0.765	0.664	0.649	0.463

In summary, the ablation study results clearly demonstrate that the proposed DFRNet backbone, C2fAttention block, SPPF module, and DPAM neck network each significantly contribute to performance improvements, collectively enabling DABD-Net’s efficient and precise drill bit damage detection capabilities.

4.5 Multi-scene detection results analysis

To vividly demonstrate DABD-Net’s detection performance in complex scenarios, this section presents a visualized analysis and comparison of detection results for typical drill bit damage images under varying lighting conditions and perspectives.

Fig. 9 uses a five-bladed PDC bit to illustrate the detection results of various models in a complex, multi-target, multi-category scenario under good lighting conditions. In this scenario, DABD-Net demonstrates superior performance, accurately identifying nearly all SD and TD damages, with prediction boxes closely aligned to actual damage boundaries and consistently high confidence scores. In contrast, the baseline RT-DETR and YOLO series models detect most damages but miss a few instances. These results indicate that DABD-Net achieves the highest detection accuracy and lowest false positive rate in complex, multi-target, multi-category scenarios.



Fig. 9 Comparison of drill bit damage detection results from top view

Fig. 10 uses a different PDC bit and presents detection results from a side view, examining the models' adaptability to simultaneous changes in bit type and viewing angle. Both RT-DETR and DABD-Net successfully detect all CW damages, demonstrating excellent perspective robustness. In contrast, models such as YOLOv5, YOLOv8, YOLOv10, and YOLOv12 exhibit noticeable misses, failing to identify some damage regions, with YOLOv5 and YOLOv8 showing the most severe misses. This comparison confirms that DABD-Net exhibits stronger robustness to varying viewing angles, consistently extracting effective damage features across different perspectives.

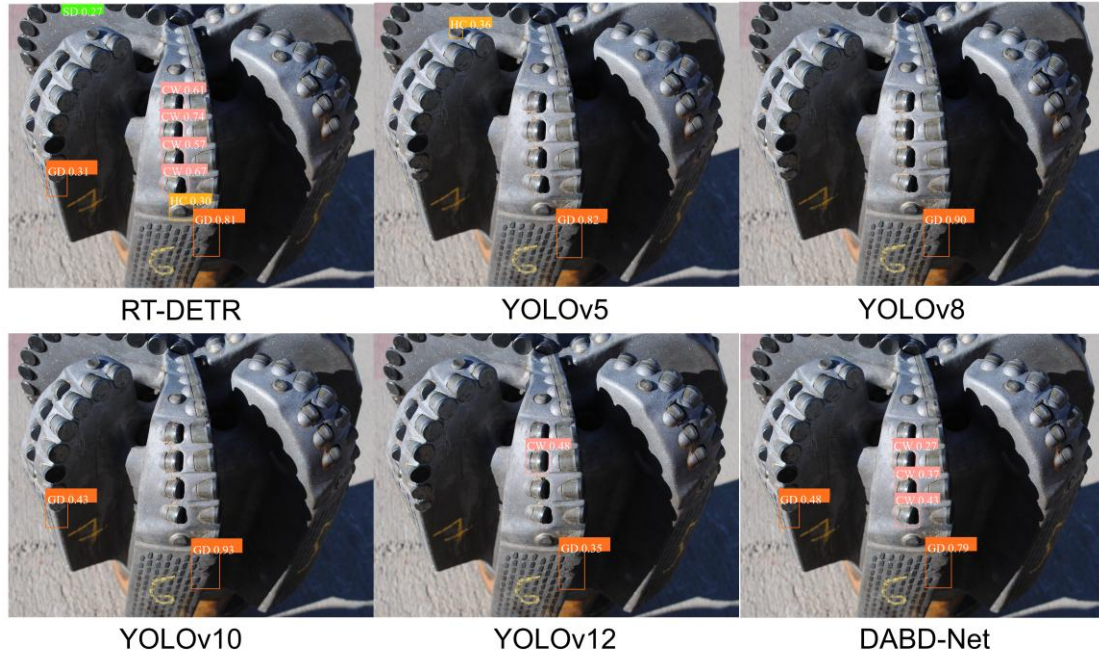


Fig. 10 Comparison of drill bit damage detection results from side view

Fig. 11 shows a detection scenario on a third drill bit under dim, non-uniform illumination, used to examine the model's robustness under low signal-to-noise imaging conditions. Such lighting is common in nighttime or shaded field environments after tripping out and poses a severe challenge to feature extraction. Under these conditions, the superiority of DABD-Net is fully demonstrated: despite the low signal-to-noise ratio, DABD-Net still successfully detects the HC that is extremely difficult to discern under dim light, with accurate localization. This capability benefits from the input-adaptive attention weighting in the DFRNet backbone, which enhances high-frequency texture features at low signal levels. In contrast, the other models, including the baseline RT-DETR and all YOLO-series models, lose the ability to capture minor thermal damage under weak illumination and exhibit severe missed detections. These results indicate that DABD-Net remains able to detect minor thermal damage under non-ideal imaging conditions such as low illumination, providing a basis for coping with the variable lighting at geothermal drilling sites.



Fig. 11 Comparison of drill bit damage detection results in dim environment

In summary, analysis of detection results across diverse scenarios demonstrates that the proposed DABD-Net outperforms other object detection models in detection accuracy, multi-target recognition, and robustness to varying perspectives and lighting conditions for PDC drill bit damage detection tasks. This highlights its significant potential for reliable application in the complex, variable environments of real-world drilling sites.

4.6 Limitations and future work

Although DABD-Net demonstrates superior performance in PDC bit damage detection for deep geothermal drilling, certain limitations remain that also indicate promising directions for future research. While the model improved the detection accuracy of highly indistinguishable HC by approximately 150%, there remains a risk of false negatives due to the low contrast of thermal damage at the microscopic level and the long-tail distribution of the data. In terms of deployment, although the PCAConv module reduces computational redundancy, high-precision inference still requires powerful GPUs. Geothermal drilling sites are typically remote, and edge devices are constrained by computing power and energy

consumption. Future work will focus on model lightweighting through pruning, quantization, and knowledge distillation to substantially reduce parameter count and power requirements while preserving sensitivity to subtle thermal damage, thereby enabling real-time inference on mobile or embedded platforms. Current experiments are primarily conducted under surface conditions. However, the exceptional ability of DABD-Net to extract microscopic textures under extremely low and nonuniform illumination carries significant engineering implications. With the increasing adoption of underbalanced drilling techniques (e.g., gas and foam drilling) in geothermal development, downhole optical visibility is gradually becoming feasible. Yet severe power constraints of downhole tools inevitably result in weak and uneven lighting. This study demonstrates that the feature-fusion mechanism of DABD-Net can effectively recover subtle thermal-damage features even under severe signal degradation. These results suggest potential value for future downhole in-situ detection; however, since all experiments in this study are based on surface, post-trip bit images, this downhole prospect still requires further validation on real downhole imagery. All experiments in this study are based on surface images of bits acquired after tripping out and have not been combined with measured downhole data; the practical effect of the detection results on inferring downhole conditions, extending bit life, and reducing non-productive time therefore remains to be examined in subsequent field application.

5 Conclusions

This study addresses the inefficiency, subjectivity, and difficulty of manual assessment in identifying microscopic thermal failure of PDC bits in deep geothermal drilling by proposing DABD-Net, an intelligent detection framework. Through construction of a dedicated dataset covering seven typical damage categories and comprehensive comparative and ablation experiments, the main conclusions are as follows:

- (1) DABD-Net achieves mAP_{0.5} of 0.652 and mAP_{0.5-0.95} of 0.477, outperforming the baseline RT-DETR and mainstream detectors including YOLOv5 and YOLOv8. Most importantly, for heat checking induced by frictional heat accumulation (the most critical geothermal failure mode), detection AP increases from 0.200 to 0.501. Recognition of corrosion wear caused by geothermal fluids is also significantly enhanced.

- (2) Ablation studies confirm that the task-specific DFRNet backbone and DPAM neck are pivotal to performance gains. These modules enable the model to simultaneously capture subtle thermal cracks and large-scale damage regions. Replacing either with corresponding components from baseline architectures causes mAP0.5 to drop by 2.0% to 2.8%. This verifies that generic detection networks are inadequate for complex surface defect analysis of geothermal bits, underscoring the necessity of the proposed specialized architecture.
- (3) Multi-scenario visualization analysis confirms the robustness and environmental adaptability of DABD-Net. Under challenging conditions such as varying viewpoints and poor illumination, DABD-Net consistently delivers stable and accurate detections with superior bounding-box alignment. In the low-light scene examined, DABD-Net was the only model to detect heat checking that all comparators missed; this stability under non-ideal imaging conditions provides favourable conditions for extending the technique towards all-weather, real-time monitoring at geothermal drilling sites.

In summary, DABD-Net not only achieves a breakthrough in detection accuracy but also provides an efficient and reliable bit-condition monitoring tool for deep geothermal development. By helping engineers identify thermal damage earlier and optimise drilling parameters accordingly, the proposed technique may contribute to extending bit life and reducing the non-productive time caused by bit failure.

Nomenclature		RT-DETR	Real-time detection transformer
F	Input feature map	YOLO	You only look once
C	Number of channels	IADC	International Association of Drilling Contractors
H	Feature-map height		
W	Feature-map width	BHA	Bottom hole assembly
F_p	Partial-channel sub-tensor	BWD	BHA whirl damage
F_{id}	Identity-channel sub-tensor	CW	Corrosion wear
f_{ca}	Channel-attention function	GD	Gauge damage
w	Attention weight vector	HC	Heat checking
σ	Sigmoid function	MD	Matrix damage
F'_p	Weighted partial feature	SD	PDC cutter surface impact damage
$\otimes$	Element-wise multiplication	TD	PDC cutter tip impact damage
f_{conv}	3×3 convolution	IoU	Intersection over union
f_{fus}	1×1 fusion convolution	DFR	Dynamic fusion residual
Y	Output feature map	C2fAttention	C2f block with attention
X'	Grouped input feature	PConv	Partial convolution
A_h	Height attention map	GAP	Global average pooling
A_w	Width attention map	SPPF	Spatial pyramid pooling-fast
Abbreviations		SPP	Spatial pyramid pooling
PDC	Polycrystalline diamond compact	CUDA	Compute unified device architecture
DABD-Net	Dynamic adaptive drill bit damage detection network	AdamW	Adam with decoupled weight decay
DFRNet	Dynamic fusion residual network	mAP	Mean average precision
PCACConv	Partial channel attention convolution	GIoU	Generalized intersection over union
EMA	Efficient multi-scale attention	AP	Average precision
DPAM	Dual-path aggregation module	FPS	Frames per second

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Conflict of interest

We declare that we have no financial or personal relationships with other people or organizations that could inappropriately influence our work.

Declaration of generative AI use

During the preparation of this work the authors used ChatGPT in order to improve language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data availability

The conventional-drilling images used in this study are from two publicly available Roboflow Universe projects, both released under the CC BY 4.0 licence (DATUM, <https://universe.roboflow.com/datum-lfd61/bit-damage>; Maged Mahmoud, <https://universe.roboflow.com/maged-mahmoud/drill-bits-failure>). The geothermal images were extracted from the publicly available Utah FORGE End-of-Well Reports, accessible through the Geothermal Data Repository. The annotations, dataset splits, and trained models generated in this study are available from the corresponding author upon reasonable request.

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