A Hybrid Artificial Intelligence Framework for OTDR-Based Anomaly Detection and Fault Classification in Optical Fibre Networks

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ABSTRACT

Optical fibre networks constitute the backbone of modern communication infrastructures, making timely and accurate fault diagnosis essential for maintaining network reliability and service availability. Although Optical Time Domain Reflectometer (OTDR) measurements are widely employed for fibre fault localization, manual interpretation of OTDR traces is labor-intensive, time-consuming, and highly dependent on expert knowledge. Existing artificial intelligence (AI)-based approaches often rely on simulated datasets, focus on a single diagnostic task, or employ a single learning model, thereby limiting their applicability in operational network environments. This paper proposes a hybrid artificial intelligence framework for automated OTDR-based fault detection and multi-class classification using real operational fibre measurements. The proposed framework integrates a convolutional autoencoder for unsupervised anomaly detection, expert-guided ground-truth labelling for reliable fault annotation, and two supervised classifiers—a Random Forest (RF) model and a one-dimensional convolutional neural network (1D-CNN)—for comparative fault classification. The framework was evaluated using 45 healthy OTDR traces for unsupervised model training and 366 operational OTDR traces representing six fault categories: healthy fibre, reflective connector fault, macro bending fault, fibre cut, high-loss splice, and end reflection. Experimental results demonstrate that both the RF and the 1D-CNN achieved an overall classification accuracy of 78% on the expert-labelled operational dataset. The 1D-CNN achieved higher weighted precision (0.80) and weighted F1-score (0.76) by automatically learning hierarchical representations directly from OTDR waveforms, while the RF provided a competitive benchmark with a macro-averaged F1-score of 0.75. The proposed framework combines anomaly detection, expert knowledge, and supervised learning within a unified diagnostic system, offering a practical and scalable solution for intelligent optical network monitoring and predictive maintenance.

1. INTRODUCTION

The continued expansion of broadband Internet services, cloud computing, fifth-generation (5G) and emerging sixth-generation (6G) communication systems, hyperscale data centers, industrial automation, and the Internet of Things (IoT) has significantly increased global dependence on optical fibre communication networks. Owing to their exceptionally high bandwidth, low attenuation, immunity to electromagnetic interference, and long transmission distance, optical fibre systems have become the backbone of modern telecommunication infrastructures. They support a wide range of critical services, including mobile communications, cloud platforms, financial systems, healthcare networks, smart cities, and industrial control systems, where uninterrupted connectivity and high service reliability are indispensable [1]–[4]. As these networks continue to increase in size and complexity, maintaining their operational integrity has become a major challenge because even localized fibre impairments can degrade network performance, interrupt communication services, and increase maintenance costs [5], [6].

Among the available diagnostic technologies, the Optical Time Domain Reflectometer (OTDR) remains the industry-standard instrument for monitoring the physical condition of optical fibre links. By transmitting short optical pulses into the fibre and analyzing the resulting Rayleigh backscattered light together with Fresnel reflections, an OTDR generates a trace that provides valuable information about attenuation characteristics and event locations along the fibre. Consequently, OTDR measurements are widely employed for fibre installation, preventive maintenance, fault localization, splice verification, connector inspection, and network troubleshooting. Their ability to identify faults such as fibre breaks, reflective connectors, splice losses, macrobending, excessive attenuation, and end reflections makes OTDR indispensable throughout the lifecycle of optical communication networks [2], [7], [8].

Despite its widespread adoption, OTDR analysis remains largely dependent on manual interpretation by experienced engineers. In practical optical networks, technicians must inspect numerous OTDR traces, distinguish genuine fault signatures from measurement noise, interpret overlapping events, and determine appropriate maintenance actions. This process becomes increasingly challenging as network size expands because manual interpretation is labor-intensive, time-consuming, and susceptible to subjective judgement. The growing volume of measurement data generated by modern communication infrastructures has therefore created an increasing demand for intelligent diagnostic systems capable of automating OTDR interpretation while maintaining high diagnostic accuracy and consistency [6], [9], [10].

Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have created new opportunities for intelligent optical network monitoring. Machine learning algorithms have been successfully applied to fault detection, event localisation, predictive maintenance, network optimization, and performance monitoring in optical communication systems. More recently, deep learning architectures such as Convolutional Neural Networks (CNNs), Autoencoders (AEs), Long Short-Term Memory (LSTM) networks, and hybrid learning frameworks have demonstrated encouraging performance by learning discriminative representations directly from OTDR signals, thereby reducing reliance on manually engineered features [3], [11]–[15]. At the same time, classical machine learning techniques, including Random Forest (RF), continue to provide competitive performance and remain attractive because of their robustness, computational efficiency, and interpretability. These developments have accelerated the transition from conventional signal-processing methods toward AI-driven optical network management capable of supporting autonomous monitoring and predictive maintenance [5], [13], [16].

Although considerable progress has been reported, several important challenges remain. First, many existing studies have been validated primarily using simulated or laboratory-generated OTDR datasets, while comparatively few have investigated intelligent fault diagnosis using operational measurements acquired from live optical fibre networks [12], [14], [17]. Models trained exclusively on simulated data may not adequately capture the variability, measurement noise, and complex fault characteristics encountered under real operating conditions, thereby limiting their practical applicability. Second, supervised learning approaches generally assume the availability of reliable labelled datasets. However, constructing high-quality OTDR benchmark datasets is difficult because accurate fault annotation requires considerable practical expertise and extensive manual interpretation by experienced engineers [15], [18]. Consequently, publicly available expert-labelled operational datasets remain limited.

Furthermore, most published studies formulate OTDR analysis solely as a supervised classification problem in which every input trace is assumed to contain a fault requiring classification. In real communication networks, however, the majority of acquired OTDR measurements correspond to healthy fibre links, making anomaly detection an essential first stage before detailed fault categorization. Although convolutional autoencoders have demonstrated promising capabilities for unsupervised anomaly detection, relatively few studies have integrated anomaly detection, expert-guided ground-truth construction, and supervised multi-class classification into a unified diagnostic framework. Likewise, objective comparisons between classical machine learning and deep learning models using identical operational datasets remain comparatively scarce [11], [16], [18]– [20]. These limitations indicate that further research is required to develop intelligent OTDR diagnostic frameworks that are both practically deployable and rigorously validated using real operational measurements.

To address these challenges, this paper proposes a Hybrid Artificial Intelligence Framework for OTDR-Based Fault Detection and Multi-Class Classification in Optical Fibre Networks. The proposed framework combines a one-dimensional Convolutional

Autoencoder (CAE) for unsupervised anomaly detection with a One-Dimensional Convolutional Neural Network (1D-CNN) for supervised multi-class fault classification. To provide a comprehensive performance assessment, a Random Forest classifier is implemented as a benchmark model using the same expert-labelled dataset. Unlike many previous studies that rely predominantly on simulated data, the proposed framework is developed and evaluated using real OTDR measurements collected from an operational optical fibre network. Following anomaly detection, each abnormal OTDR trace is manually interpreted and assigned to one of six fault categories by experienced personnel, thereby establishing a reliable ground-truth dataset for supervised learning. This integrated workflow combines unsupervised representation learning, expert-assisted annotation, and supervised classification within a single intelligent diagnostic framework designed for practical optical network monitoring.

The principal contributions of this paper are summarized as follows:

1. A hybrid artificial intelligence framework integrating convolutional autoencoder-based anomaly detection with supervised multi-class fault classification for intelligent OTDR analysis.

2. An expert-guided ground-truth labelling methodology for constructing a reliable benchmark dataset from operational OTDR measurements acquired from a live optical fibre communication network.

3. A comparative evaluation of Random Forest and One-Dimensional Convolutional Neural Network classifiers using identical expert-labelled operational datasets to assess the relative performance of classical machine learning and deep learning approaches.

4. Comprehensive experimental validation using real-world OTDR measurements, demonstrating the effectiveness of the proposed framework for automated fault diagnosis and intelligent optical network monitoring.

The remainder of this paper is organized as follows. Section II reviews recent advances in AI-assisted OTDR fault diagnosis and optical network monitoring. Section III presents the proposed hybrid framework, including dataset preparation, signal standardization, anomaly detection, expert ground-truth labelling, and supervised classification. Section IV describes the experimental setup and presents the performance evaluation of the proposed models. Section V discusses the practical implications of the findings, while Section VI concludes the paper and outlines directions for future research.

2. RELATED WORK

Recent advances in artificial intelligence have significantly improved the automation of Optical Time Domain Reflectometer (OTDR) signal interpretation for optical fibre fault detection and diagnosis. Research efforts have focused on applying both classical machine learning and deep learning techniques to overcome the limitations of manual OTDR trace analysis, particularly in large-scale optical communication networks. Despite these developments, several challenges remain regarding anomaly detection, feature representation, dataset availability, and model generalization.

2.1 Evolution of artificial intelligence for OTDR-based fault diagnosis

Optical Time Domain Reflectometry (OTDR) has long served as the primary diagnostic technique for monitoring the physical condition of optical fibre communication networks. By analyzing the backscattered and reflected optical signals generated along a fibre link, OTDR enables the detection and localization of faults such as fibre breaks, splice losses, connector defects, macrobending, and end reflections. Traditionally, the interpretation of OTDR traces has relied on signal processing techniques and manual inspection by experienced technicians, who identify fault events based on characteristic attenuation profiles and reflection patterns. Although these approaches have proven effective for routine maintenance, they are often labor-intensive, time-consuming, and susceptible to inconsistencies when applied to large-scale optical networks containing thousands of fibre links [21], [22].

The increasing complexity of modern communication infrastructures has stimulated the adoption of machine learning techniques to improve the efficiency and reliability of OTDR fault diagnosis. Early intelligent diagnostic systems employed supervised learning algorithms such as Support Vector Machines (SVMs), Decision Trees (DTs), Random Forests (RFs), Artificial Neural Networks (ANNs), and ensemble learning methods to classify fibre faults using manually engineered signal features extracted from OTDR traces. These approaches reduced dependence on manual interpretation and demonstrated encouraging performance for fault identification; however, their effectiveness remained highly dependent on the quality of handcrafted features and expert domain knowledge [23]– [25].

Recent advances in deep learning have significantly transformed intelligent OTDR analysis by enabling automatic feature extraction directly from raw measurement signals. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, autoencoders, and attention-based architectures have demonstrated superior capability in learning complex spatial and temporal representations of OTDR traces without extensive feature engineering. As a result, deep learning models have achieved substantial improvements in fault detection, localization, anomaly identification, and multi-class classification, particularly under challenging conditions involving measurement noise and complex fault patterns [9],[26]– [29].

More recently, research has shifted toward hybrid artificial intelligence frameworks that integrate complementary learning paradigms within a unified diagnostic pipeline. These frameworks combine unsupervised anomaly detection, supervised fault classification, ensemble learning, attention mechanisms, and data augmentation strategies to improve robustness and generalization across diverse network conditions. Hybrid models seek to exploit the strengths of individual algorithms while mitigating their limitations, making them increasingly attractive for practical optical network monitoring. More recently, Transformer-based architectures and foundation-model-inspired approaches have begun to emerge for optical network monitoring, demonstrating promising capabilities for anomaly detection, fault localization, and intelligent decision support in large-scale communication infrastructures [9],[10],[14], 30].

Beyond hybrid learning, the emergence of foundation models and generative artificial intelligence has opened new research directions for optical network management. Recent studies have investigated large-scale representation learning, transformer-based architectures, and generative models for OTDR data augmentation, fault prediction, and intelligent decision support. Although these approaches remain in the early stages of application to optical fibre diagnostics, they illustrate the continuing evolution of AI-driven network monitoring toward more autonomous, scalable, and adaptive maintenance systems [32], [33].

Overall, the evolution from conventional signal processing to machine learning, deep learning, hybrid artificial intelligence, and emerging foundation models demonstrates a clear shift toward increasingly intelligent and automated OTDR analysis. Nevertheless, challenges associated with operational data availability, expert-verified ground-truth labels, and integrated anomaly detection remain insufficiently addressed. These challenges motivate the more focused review presented in the following subsections, which examine recent advances in autoencoder-based anomaly detection, CNN-based fault classification, hybrid AI frameworks, and benchmark machine learning models.

2.2 Autoencoder-Based Anomaly Detection

Autoencoders have emerged as an effective approach for unsupervised anomaly detection in OTDR-based optical network monitoring because they learn compact representations of normal fibre behavior without requiring labelled fault data. During inference, healthy OTDR traces are reconstructed with low error, whereas abnormal traces typically exhibit larger reconstruction errors, providing a practical basis for anomaly detection. This reconstruction-based strategy is particularly well suited to operational optical networks, where healthy fibre measurements substantially outnumber fault events. Recent studies have further shown that convolutional and denoising autoencoders can suppress measurement noise while preserving fault-related characteristics, thereby improving anomaly detection performance and generating informative feature representations for subsequent fault localisation and classification [9],[36].

Several autoencoder variants have been investigated for OTDR analysis. Denoising Convolutional Autoencoders (DCAEs) improve robustness by suppressing measurement noise while preserving important fault characteristics. For example, Abdelli *et al.* combined a DCAE with a Bidirectional Long Short-Term Memory (BiLSTM) network for fault detection and localisation, demonstrating improved diagnostic performance under noisy operating conditions [22]. Building on this concept, Convolutional Autoencoders (CAEs) have been widely adopted for learning hierarchical representations directly from OTDR traces through convolutional feature extraction, thereby reducing reliance on manually engineered features. More recent studies have also explored generative learning techniques to augment scarce OTDR datasets and improve model robustness, particularly under conditions of class imbalance and limited labelled operational data. These developments suggest that reconstruction-based learning and generative modelling will continue to play an increasingly important role in intelligent optical fibre fault diagnosis [14]– [36].

Recent research has increasingly adopted reconstruction-based diagnosis, in which an input OTDR trace is compared with its reconstructed counterpart to identify abnormal network conditions. Under this paradigm, autoencoders are trained exclusively on healthy fibre measurements so that normal traces can be reconstructed with minimal error, whereas anomalous traces produce significantly larger reconstruction errors. A predefined reconstruction-error threshold is then used to distinguish healthy from abnormal measurements before the latter are forwarded to a supervised classifier for detailed fault identification. This two-stage strategy has demonstrated improved robustness for practical optical network monitoring because it reflects the natural imbalance between healthy and faulty OTDR measurements encountered in operational environments. More recently, researchers have combined autoencoders with recurrent neural networks, attention mechanisms, and generative learning techniques to further improve anomaly detection accuracy, enhance feature representation, and alleviate the challenges associated with limited and imbalanced OTDR datasets [14],[22],[34].

Despite these encouraging developments, several important limitations remain. A large proportion of the published studies have been validated using simulated or laboratory-generated OTDR signals, with relatively few investigations evaluating reconstruction-based anomaly detection under real operational network conditions. Moreover, anomaly detection is frequently treated as an independent task without establishing reliable expert-derived ground-truth labels for subsequent supervised fault classification. As a result, the complete diagnostic workflow—from anomaly detection through expert annotation to multi-class fault classification—has received comparatively limited attention. Addressing these gaps forms one of the principal motivations for the hybrid artificial intelligence framework proposed in this study, which integrates convolutional autoencoder-based anomaly detection, expert-guided ground-truth labelling, and supervised multi-class classification using operational OTDR measurements collected from a live optical fibre network.

2.3 CNN-based OTDR classification

Convolutional Neural Networks (CNNs) have become one of the most widely adopted deep learning models for OTDR fault classification because they automatically learn hierarchical feature representations directly from raw signal data, thereby reducing dependence on handcrafted feature extraction. Early CNN-based studies demonstrated that convolutional architectures could accurately identify reflective events and common fibre faults while exhibiting greater robustness to signal noise than traditional machine learning methods [26],[37].

Recent research has focused on improving CNN performance through the development of more sophisticated network architectures tailored to the characteristics of OTDR signals. Among these, One-Dimensional Convolutional Neural Networks (1D-CNNs) have attracted considerable attention because they operate directly on one-dimensional OTDR traces, preserving the sequential structure of fibre measurements while reducing computational complexity and eliminating the need to transform signals into two-dimensional representations. These advantages make 1D-CNNs particularly suitable for real-time fault diagnosis in operational optical networks [26], [38]. To further enhance feature extraction, researchers have proposed multi-scale CNN architectures that employ convolutional kernels of different receptive fields to capture both localized fault signatures and long-range attenuation characteristics within OTDR traces. Such multi-scale feature learning has been shown to improve classification robustness, particularly for complex fault scenarios involving overlapping events and varying signal characteristics [29],[39].

Several studies have combined convolutional neural networks with recurrent architectures to exploit the complementary strengths of spatial feature extraction and sequential learning. Hybrid CNN-LSTM and CNN-BiLSTM models have demonstrated improved capability for modelling complex fault patterns by integrating convolutional feature learning with temporal dependency analysis, resulting in more robust fault classification under noisy conditions and in the presence of multiple fault events [22], [30]. More recently, attention mechanisms have been incorporated into CNN-based frameworks to enable adaptive feature weighting, allowing models to focus on diagnostically significant regions of OTDR traces while suppressing redundant or irrelevant information. These developments have further improved classification accuracy and model robustness, particularly for complex operational scenarios involving heterogeneous fault characteristics [33], [34].

Overall, recent studies demonstrate a clear evolution from conventional CNN models toward multi-scale, recurrent, and attention-enhanced deep learning architectures. Despite these advances, many reported results have been obtained using simulated or laboratory-generated OTDR datasets, while comparatively few investigations have evaluated these models using expert-labelled operational measurements acquired from live optical fibre networks. Consequently, further validation under realistic field conditions remains essential for assessing the practical applicability and generalization capability of intelligent OTDR diagnostic systems.

2.4 Hybrid artificial intelligence framework

Recent advances in intelligent OTDR fault diagnosis have increasingly favored hybrid artificial intelligence (AI) frameworks that combine complementary learning algorithms within a unified diagnostic pipeline. Rather than relying on a single predictive model, these approaches integrate the representation-learning capability of deep neural networks with sequential learning, attention mechanisms, or ensemble techniques to improve diagnostic robustness and generalization. By exploiting the strengths of different architectures, hybrid models have demonstrated improved adaptability to complex OTDR signals and have emerged as a promising direction for intelligent optical network monitoring [22],[34].

Several studies have combined convolutional neural networks with recurrent architectures such as Long Short-Term Memory (LSTM) and Bidirectional Gated Recurrent Unit (BiGRU) networks, where convolutional layers learn local fault characteristics while recurrent layers capture temporal dependencies within OTDR traces. More recently, researchers have incorporated attention mechanisms and Transformer-inspired architectures to enhance feature representation by enabling the network to focus selectively on diagnostically relevant regions of the signal. These developments have improved classification robustness, particularly under noisy conditions and in the presence of multiple fault events, and generally outperform conventional standalone CNN models [14],[32],[33],[37]. These architectures have generally demonstrated improved classification performance compared with conventional standalone CNN models.

Hybrid learning has also been extended to anomaly detection through the integration of convolutional autoencoders (CAEs) with supervised classification models. In these frameworks, the autoencoder first identifies abnormal OTDR traces by analyzing reconstruction error, after which the detected anomalies are forwarded to supervised classifiers, including convolutional and recurrent neural network models, for detailed fault categorization. Separating anomaly detection from fault classification reduces unnecessary computational effort while allowing each stage to be optimized independently. Recent studies have shown that this two-stage learning strategy improves diagnostic robustness and provides a more practical solution for intelligent optical network monitoring [22],[34].

At the same time, growing attention has been directed toward data-centric learning strategies aimed at overcoming the limited availability of labelled operational OTDR datasets. Recent studies have investigated generative artificial intelligence and data augmentation techniques to synthesize realistic fault patterns, improve class balance, and enhance the generalization capability of supervised learning models trained on relatively small datasets. These approaches have demonstrated considerable potential for improving diagnostic performance while reducing dependence on costly manual data collection and annotation [14],[33].

Despite these advances, most hybrid diagnostic frameworks continue to be validated using simulated datasets or relatively simple fault scenarios, whereas comparatively few studies have incorporated expert-derived ground-truth labels obtained from operational optical fibre networks. Furthermore, direct comparative evaluations between hybrid deep learning frameworks and well-established benchmark machine learning algorithms remain limited. These observations reinforce the need for an integrated diagnostic framework that combines unsupervised anomaly detection, expert-guided ground-truth construction, and supervised multi-class fault classification using real OTDR measurements acquired from operational fibre communication networks.

2.5 Classical machine learning benchmarks

Although deep learning has become the predominant approach for intelligent OTDR fault diagnosis, classical machine learning algorithms continue to play an important role as benchmark models. Their relatively low computational complexity, ease of implementation, and model interpretability make them attractive for practical deployment, particularly in situations where labelled datasets are limited or computational resources are constrained. Moreover, these algorithms provide valuable reference points for assessing whether the increased complexity of deep learning architectures translates into meaningful improvements in diagnostic performance [37], [22].

Among the classical learning algorithms, Random Forest (RF) has been widely adopted because of its robustness against overfitting, ability to model nonlinear relationships, and effectiveness in handling high-dimensional feature spaces through ensemble decision trees. Recent studies have reported that RF achieves competitive fault classification performance when discriminative features are extracted from OTDR attenuation profiles, reflection peaks, and event characteristics [37]. Likewise, Support Vector Machines (SVMs) remain effective for both binary and multi-class fibre fault classification because of their strong generalization capability, particularly when training data are limited. Decision Trees (DTs), although comparatively simpler, offer transparent decision rules that facilitate model interpretation and remain useful for diagnostic decision support. Consequently, many recent comparative studies continue to include RF, SVM, and DT as benchmark algorithms when evaluating the effectiveness of more sophisticated deep learning and hybrid AI frameworks [39],[40].

More recently, ensemble learning algorithms such as Gradient Boosting, Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM) have attracted increasing attention because of their strong predictive performance, computational efficiency, and ability to model complex nonlinear relationships. These methods have demonstrated competitive performance across a wide range of fault diagnosis applications and are increasingly adopted as benchmark models in intelligent optical network monitoring. Their ability to achieve high classification accuracy while requiring comparatively lower computational resources makes them attractive alternatives for evaluating the effectiveness of deep learning architectures [41], [37]. Consequently, many recent comparative studies include ensemble learning algorithms alongside CNN-based models to determine whether the additional complexity of deep learning provides statistically significant improvements in diagnostic performance under realistic operating conditions.

Overall, classical machine learning algorithms continue to serve as valuable benchmark models for OTDR fault diagnosis. Their inclusion provides an objective basis for comparing model accuracy, computational efficiency, and generalization capability against more sophisticated deep learning and hybrid AI frameworks. Such comparative evaluations remain essential for identifying diagnostic approaches that are not only accurate but also computationally practical for deployment in operational optical fibre communication networks.

2.6 Critical Analysis and Research Gap

The reviewed literature demonstrates that artificial intelligence has substantially advanced automated OTDR fault diagnosis, with many recent studies reporting classification accuracies exceeding 95% under controlled experimental conditions. While these findings highlight the potential of deep learning for intelligent optical network monitoring, they should be interpreted with caution. A considerable proportion of the published research has been validated using simulated OTDR traces, laboratory-generated datasets, or relatively simple fault scenarios that may not adequately represent the variability encountered in operational optical fibre networks. In practical deployments, OTDR measurements are often affected by measurement noise, varying attenuation characteristics, environmental influences, and multiple concurrent fault events, all of which present additional challenges for reliable fault diagnosis. Consequently, the generalization capability of many reported models under real-world operating conditions remains insufficiently established [22],[32],[37].

Another important limitation is that most existing studies formulate OTDR analysis primarily as a supervised classification problem, implicitly assuming that every input trace contains a fault requiring identification. In operational optical networks, however, healthy fibre measurements typically constitute the majority of acquired OTDR data, making anomaly detection a necessary preliminary stage before detailed fault classification. Although recent advances in autoencoder-based learning have demonstrated the effectiveness of reconstruction-based anomaly detection, relatively few investigations have integrated unsupervised anomaly detection, expert-guided ground-truth labelling, and supervised multi-class classification within a unified diagnostic framework evaluated using operational OTDR measurements [22].

The literature reviewed in this section demonstrates that artificial intelligence has substantially advanced automated OTDR fault diagnosis. Nevertheless, several important challenges remain unresolved. One of the most significant limitations is the scarcity of expert-verified operational OTDR datasets. The effectiveness of supervised learning depends fundamentally on the quality of ground-truth labels, yet many published studies provide limited information regarding the annotation process or rely primarily on simulated labels generated under controlled laboratory conditions. Consequently, practical reliability and generalization capability of many proposed diagnostic models remain difficult to assess under realistic operating environments. Recent surveys and experimental studies consistently identify the availability of operational datasets, expert-guided annotation, robust hybrid learning strategies, and comprehensive validation using real optical communication networks as critical priorities for advancing intelligent optical network monitoring [42],[22].

Motivated by these observations, the present study proposes a hybrid artificial intelligence framework that integrates convolutional autoencoder-based anomaly detection, expert-guided ground-truth labelling, and supervised multi-class fault classification using both a One-Dimensional Convolutional Neural Network (1D-CNN) and a Random Forest benchmark classifier. Unlike many previous investigations, the proposed framework is developed and evaluated using operational OTDR measurements collected from a live optical fibre communication network. By combining unsupervised anomaly detection, reliable expert annotation, benchmark machine learning, and deep learning within a unified diagnostic pipeline, the proposed framework addresses several limitations identified in the recent literature while providing a practical and reproducible solution for intelligent optical fibre fault diagnosis.

Table 1: Comparison of Recent Artificial Intelligence Approaches for OTDR Fault Diagnosis (2022–2026)

Authors	AI Technique	Dataset	Major Limitation
Abdelli *et al.* 2022	Denoising Convolutional Autoencoder + BiLSTM	Simulated noisy OTDR traces	Validated mainly on simulated noisy signals with limited operational evaluation.
Abdelli *et al.* 2022	CNN	Simulated OTDR traces	Focused primarily on reflective event detection rather than comprehensive fault diagnosis.
Abdelli *et al.* 2022	BiGRU + Autoencoder	Passive Optical Network OTDR dataset	Designed specifically for PON environments with limited fault diversity.
Yang *et al.* 2023	Multi-scale CNN–BiLSTM	Public OTDR dataset	Performance evaluated mainly on benchmark datasets rather than operational networks.
Titouni *et al.* 2023	CNN + Ensemble Learning	Experimental OTDR dataset	Limited validation using real field measurements.
Straub *et al.* 2024	Machine Learning Framework	Passive Optical Network OTDR dataset	Focused on PON diagnosis with restricted fault scenarios.
Soothar *et al.* 2024	Random Forest, SVM, XGBoost Comparison	Experimental dataset	Relied on handcrafted features and limited signal diversity.
Reyes-Vera *et al.* 2024	Machine Learning for Optical Fibre Sensing (Review)	Multiple datasets	Review paper; no unified diagnostic framework or experimental validation.
Healy *et al.* 2025	Generative AI for Failure Identification	Operational OTDR dataset	Emphasized data augmentation and failure analysis rather than integrated fault diagnosis.
Recent Generative AI Studies 2025	Conditional GAN / Conditional VAE	Synthetic and operational OTDR datasets	Primarily addressed dataset imbalance; limited end-to-end deployment validation.
Recent Hybrid AI Studies 2025–2026	CNN–Transformer / Attention-Based Hybrid Networks	Mixed OTDR datasets	Hybrid architectures remain largely validated using laboratory or simulated datasets.
Proposed Framework (This Study) 2026	Convolutional Autoencoder + Expert Ground-Truth Labelling + Random Forest + 1D-CNN	45 Healthy and 366 Operational OTDR Traces from a Live Optical Fibre Network	Integrates unsupervised anomaly detection, expert-guided dataset construction, and comparative evaluation of classical and deep learning models using operational OTDR measurements.

The literature reviewed in this section demonstrates significant progress in the application of artificial intelligence to OTDR-based fault diagnosis. However, existing studies remain constrained by the limited use of operational datasets, the scarcity of expert-verified ground-truth labels, and the lack of integrated frameworks that combine anomaly detection with supervised multi-class classification. These limitations provide the motivation for the hybrid artificial intelligence framework presented in the next section, which integrates convolutional autoencoder-based anomaly detection, expert-guided ground-truth construction, Random Forest benchmarking, and One-Dimensional CNN classification using operational OTDR measurements collected from a live optical fibre network.

3. Proposed hybrid artificial intelligence framework

This study proposes a three-stage hybrid artificial intelligence framework for automated fault detection and multi-class classification of Optical Time Domain Reflectometer (OTDR) signals. The framework combines unsupervised deep learning, expert-guided data annotation, classical machine learning, and supervised deep learning to improve the reliability of fibre fault diagnosis under operational conditions.

Unlike many existing approaches that perform direct supervised classification, the proposed framework first distinguishes normal and abnormal OTDR traces through unsupervised anomaly detection before conducting detailed fault classification. This strategy closely reflects practical network maintenance procedures, where healthy fibres constitute the majority of monitored links and only abnormal traces require detailed investigation.

3.1 OTDR Dataset preparation

Two independent OTDR datasets were employed to develop and evaluate the proposed framework. The first dataset consisted of 45 healthy OTDR traces acquired from fault-free single-mode optical fibre links operating at a wavelength of 1550 nm. These traces represented the normal operating behavior of the optical transmission system and were used exclusively for training the convolutional autoencoder.

Because OTDR measurements were obtained from fibre links of varying lengths, the acquired traces differed in signal size. To ensure compatibility with deep learning algorithms, every OTDR trace was standardized to a fixed length of 24,000 samples. Signals exceeding this length were cropped, whereas shorter traces were zero-padded at the end. This preprocessing strategy preserved the original waveform characteristics while providing a uniform input dimension for all learning models.

Following anomaly detection, every operational OTDR trace was independently examined by an experienced fibre-optic engineer. Fault categories were assigned through manual interpretation of the OTDR signatures using standard engineering practice. The expert-generated annotations constituted the ground-truth labels for supervised learning and performance evaluation. Six operational fault categories were defined, namely healthy fibre, reflective connector fault, macrobending fault, fibre cut, high-loss splice, and end reflection.

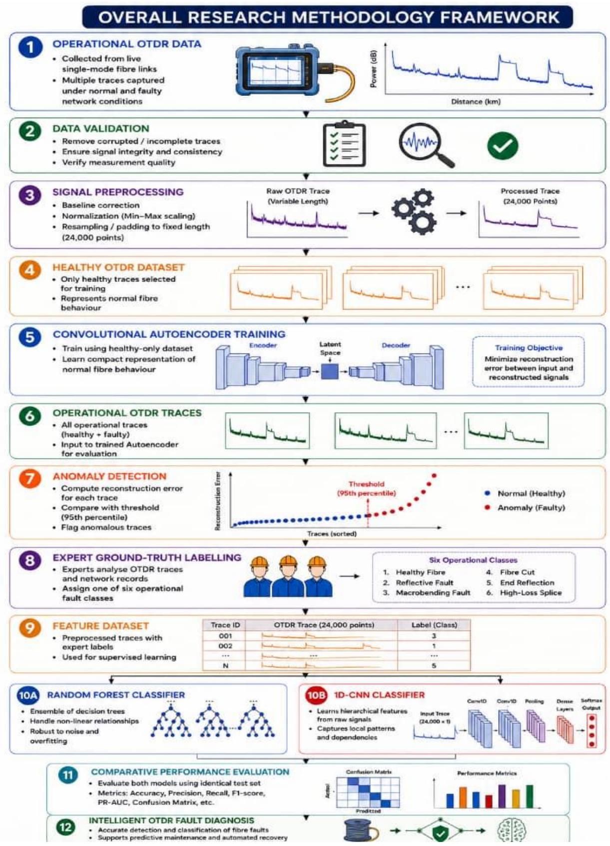

Fig. 1: Overall Architecture of the Proposed Hybrid AI Framework

3.2 Stage I: Convolutional autoencoder for anomaly detection

The first stage of the proposed framework employs a one-dimensional Convolutional Autoencoder (CAE) to distinguish normal OTDR traces from abnormal network conditions. Autoencoders are unsupervised neural networks designed to reconstruct input signals after compressing them into a lower-dimensional latent representation. Since the CAE is trained solely on healthy OTDR traces, it learns the intrinsic characteristics of normal fibre behavior without requiring labelled fault samples.

The encoder consists of successive one-dimensional convolutional and max-pooling layers that progressively compress the input signal into a compact latent representation. The decoder reconstructs the signal through convolutional and up-sampling operations, producing an approximation of the original OTDR trace.

During inference, each operational OTDR trace is passed through the trained autoencoder, and the reconstruction error is computed using the Mean Squared Error (MSE) between the original and reconstructed signals. Healthy traces generally exhibit low reconstruction errors because they closely resemble the training distribution, whereas abnormal traces produce significantly higher reconstruction errors due to the presence of structural deviations introduced by fibre faults.

An anomaly threshold was established using the 95th percentile of the reconstruction error distribution obtained from the healthy training dataset. Operational traces with reconstruction errors exceeding this threshold were classified as anomalous and forwarded to the subsequent classification stage. This approach minimizes false alarms while ensuring that potential fibre faults are retained for detailed analysis.

The architecture of the convolutional autoencoder is presented in Fig. 2, while the detailed network configuration is summarized in Table 2.

Table 2: Convolutional Autoencoder Architecture

Parameter	Value Used
Training dataset	45 healthy OTDR traces
Input signal length	24,000 samples
Input shape	(24,000 × 1)
Autoencoder type	One-Dimensional Convolutional Autoencoder
Optimizer	Adam
Loss function	Mean Squared Error (MSE)
Activation function (hidden layers)	ReLU
Activation function (output layer)	Sigmoid
Number of epochs	200
Batch size	4
Validation split	20%
Training samples	36
Validation samples	9
Shuffle	True
Callbacks	EarlyStopping, ReduceLROnPlateau, ModelCheckpoint
EarlyStopping patience	20 epochs
ReduceLROnPlateau factor	0.5
ReduceLROnPlateau patience	8 epochs

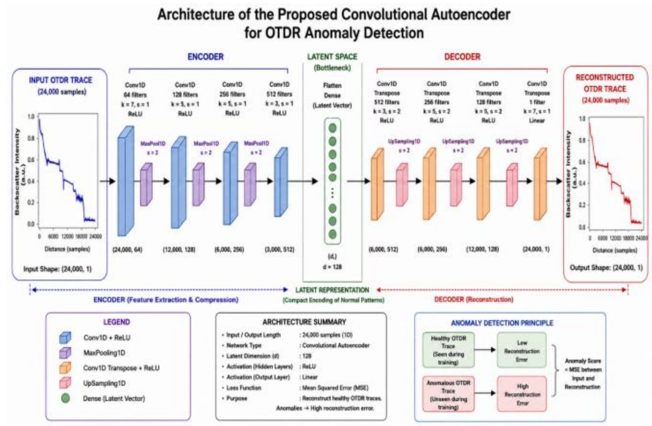

Fig. 2: Architecture of the One-Dimensional Convolutional Autoencoder

3.3 Expert ground-truth labelling

Unlike many existing studies that rely on simulated fault scenarios or automatically generated labels, this work adopts an expert-guided annotation strategy to establish reliable ground truth for supervised learning.

Each anomalous OTDR trace identified during Stage I was manually interpreted by an experienced fibre-optic engineer. The interpretation considered characteristic OTDR signatures, including reflective peaks, localized attenuation, abrupt signal termination, splice loss, and end-of-fibre reflections. Based on these characteristics, every trace was assigned to one of six predefined fault categories.

This expert-guided labelling process ensured that the supervised learning algorithms were trained using physically meaningful fault classes derived from operational measurements rather than synthetic approximations. Consequently, the resulting classifiers better reflect practical deployment scenarios encountered in real optical communication networks.

3.4 Stage II: Random Forest benchmark classification

To establish a baseline for comparative evaluation, a Random Forest classifier was implemented using the expert-labelled operational dataset. Random Forest is an ensemble learning algorithm that constructs multiple decision trees using bootstrap sampling and random feature selection before aggregating their predictions through majority voting.

To quantitatively characterize the localized attenuation drops and reflective power surges across the traces, two discriminative features were extracted: the Color Drop Metric (M_{drop}) and the Color Spike Metric (M_{spike}). Let $S = [s_1, s_2, \dots, s_N]$ represent the normalized trace amplitude vector of length N, where $s_i \in [0,1]$ corresponds to the signal power at discrete index i.

1. **Color Drop Metric (M_{drop}):** Quantifies the maximum abrupt, non-reflective power drop across a localized spatial evaluation window w, effectively capturing localized attenuation events such as macrobends and high-loss non-reflective splices. It is defined as:

$$M_{\text{drop}} = \max_{1 \le i \le N-w} (s_i - s_{i+w}) \tag{1}$$

2. **Color Spike Metric (M_{spike}):** Quantifies the maximum positive power excursion relative to the local moving average baseline μ_i, isolating sharp localized reflection peaks caused by mechanical connectors and optical fiber end-faces. It is formulated as:

$$M_{\text{spike}} = \max_{1 \le i \le N} (s_i - \mu_i) \tag{2}$$

where $\mu_i = \frac{1}{w}\sum_{k=i-w/2}^{i+w/2} s_k$ represents the local background signal floor centered at position i.

The extracted feature pairs $(M_{\text{drop}}, M_{\text{spike}})$ were utilized as two-dimensional input vectors for classification. The dataset was divided into training and testing subsets using an 80:20 stratified split to preserve the underlying class distribution. The Random Forest classifier was configured with 100 decision trees ($n_estimators = 100$) alongside balanced class weighting ($class_weight = 'balanced'$) to adjust penalization inversely proportional to class frequencies. The Random Forest model serves as a conventional machine learning benchmark against which the deep learning classifier can be objectively evaluated.

3.5 Stage III: One-dimensional convolutional neural network classification

The final stage of the proposed framework employs a One-Dimensional Convolutional Neural Network (1D-CNN) to perform supervised multi-class classification of the expert-labelled OTDR traces. Each OTDR measurement was standardized to a fixed length of 24,000 samples and represented as a one-dimensional input vector with a single signal channel. The resulting input dimension to the network was therefore $(24{,}000 \times 1)$.

The proposed 1D-CNN consists of three successive convolutional feature-extraction blocks. The first convolutional layer employs 64 filters with a kernel size of 7, followed by max-pooling with a pool size of 2. The second convolutional layer uses 128 filters with a kernel size of 5 and is similarly followed by max-pooling. The third convolutional layer employs 256 filters with a kernel size of 3, followed by a final max-pooling operation. ReLU activation functions are used in the convolutional layers to introduce nonlinear feature learning.

Following convolutional feature extraction, the resulting feature maps are flattened and passed to a fully connected layer containing 512 neurons with ReLU activation. A dropout layer with a rate of 0.5 is incorporated to reduce overfitting, followed by a second fully connected layer containing 128 neurons. The final output layer consists of six neurons with softmax activation, corresponding to the six predefined OTDR classes: Healthy, Reflective Connector, Macrobend, Fibre Cut, High-Loss Splice, and End Reflection.

This architecture enables the network to learn hierarchical representations directly from the standardized OTDR waveforms while preserving the sequential structure of the measurements. Unlike the Random Forest benchmark, which relies on explicitly extracted signal features, the 1D-CNN automatically learns discriminative features during training and uses these representations to perform multi-class fault classification.

To compensate for the unequal distribution of fault classes, class-balanced weighting was incorporated during network training. Model optimization was performed using the Adam optimizer with the sparse categorical cross-entropy loss function over 45 training epochs using a batch size of 16.

Compared with conventional machine learning approaches, the proposed 1D-CNN automatically learns hierarchical representations directly from OTDR signals, eliminating the need for extensive manual feature engineering. This capability enables the network to capture subtle waveform characteristics associated with different fibre fault types while maintaining computational efficiency suitable for intelligent optical network monitoring.

The complete architecture of the 1D-CNN is illustrated in Fig. 3, and its detailed layer configuration and summarized in Table 3.

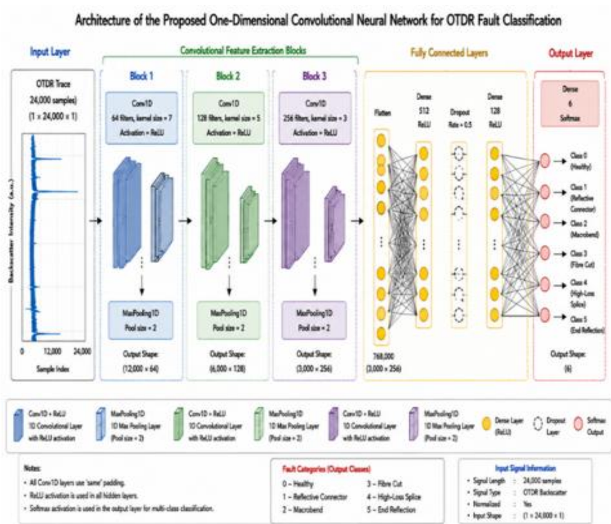

Fig. 3: Architecture of the Proposed One-Dimensional Convolutional Neural Network

Table 3: One-Dimensional CNN Architecture Used for Multi-Class Fault Classification

Parameter	**Value**
Optimiser	Adam
Loss Function	Sparse Categorical Cross-Entropy
Activation Function	ReLU (Hidden Layers)
Output Activation	Softmax (Classification Layer)
Batch Size	16
Number of Epochs	25
Learning Rate	0.001 (Standard default for Keras Adam optimiser)
Dropout Rate	0.2 (Applied after both Convolutional blocks)

4. Experimental Results and Discussion

This section evaluates the effectiveness of the proposed hybrid artificial intelligence framework using operational OTDR measurements collected from a live optical fibre network. Performance is assessed for both the unsupervised anomaly detection stage and the supervised multi-class classification stage. The evaluation also compares the proposed one-dimensional convolutional neural network (1D-CNN) with a Random Forest classifier trained on the same expert-labelled dataset.

4.1 Experimental setup

The proposed framework was implemented in Python using TensorFlow, Scikit-learn, NumPy, Pandas, and Matplotlib. Model development and evaluation were conducted on a workstation equipped with an Intel Core processor and 16 GB RAM. The convolutional autoencoder was trained exclusively on 45 healthy OTDR traces, while the supervised classifiers were developed using 366 expert-labelled operational OTDR traces representing six fault categories.

To ensure a fair comparison, both the Random Forest and 1D-CNN classifiers employed an identical 80:20 stratified train-test split. Class imbalance was addressed through balanced class weighting during training.

4.2 Performance of the convolutional autoencoder

The first stage of the proposed framework focuses on distinguishing healthy OTDR traces from abnormal network conditions. After training exclusively on healthy fibre measurements, the convolutional autoencoder learned the characteristic representation of normal OTDR signals. Healthy traces were reconstructed with relatively low reconstruction errors, whereas abnormal traces containing reflective events, splice losses, fibre cuts, and macrobending produced substantially higher reconstruction errors. This difference indicates that the autoencoder was able to identify deviations from the learned representation of normal fibre behavior and served as the anomaly-detection stage of the proposed framework.

Figure 4 presents a representative comparison between an original healthy OTDR trace and its reconstructed output. The reconstructed signal closely follows the overall attenuation profile of the original trace across most of the measurement distance, including the initial launch region and the gradual reduction in backscattered power. The agreement between the two traces indicates that the autoencoder captured the dominant characteristics of the healthy fibre signal. Some differences are visible toward the latter portion of the trace, where the original signal exhibits greater measurement fluctuations and end-of-link variations. These local differences are expected to contribute to the reconstruction error while the overall signal structure remains well preserved.

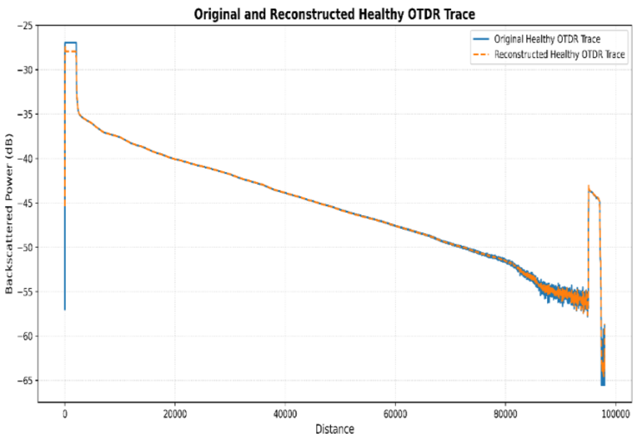

Fig. 4: Original and reconstructed healthy OTDR trace obtained using the trained convolutional autoencoder.

The effectiveness of the autoencoder was further evaluated using the reconstruction-error distribution obtained from the operational OTDR dataset. Healthy fibre traces consistently produced lower reconstruction errors than abnormal traces, allowing a suitable threshold to be established for anomaly detection. Traces with reconstruction errors exceeding the selected threshold were classified as anomalous and subsequently forwarded to the expert-guided ground-truth labelling stage for detailed fault categorization.

4.3 Original and reconstructed healthy OTDR trace using the convolutional autoencoder

The reconstruction error distribution obtained from the operational dataset is presented in Fig. 5. A threshold corresponding to the 95th percentile of the healthy reconstruction error distribution was adopted to separate normal and abnormal traces. Signals exceeding this threshold were classified as anomalous and forwarded to the supervised classification stage.

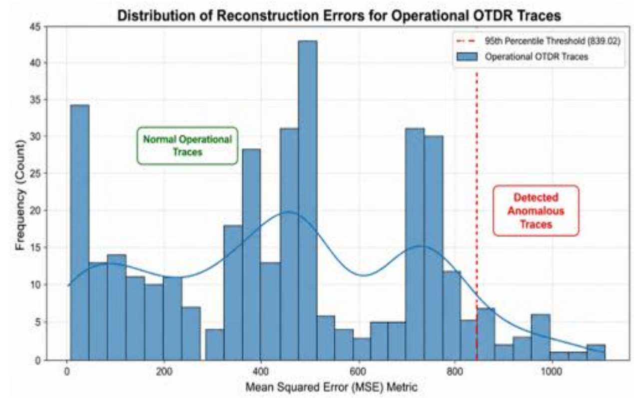

Fig. 5: Distribution of reconstruction errors and selected anomaly threshold

The anomaly detection stage substantially reduced the number of traces requiring manual examination while preserving all abnormal network conditions for subsequent expert verification. This demonstrates the suitability of convolutional autoencoders as an intelligent screening mechanism for large-scale optical fibre monitoring systems.

4.4 Random Forest classification performance

To establish a baseline for comparison, a Random Forest classifier was trained using expert-labelled OTDR features extracted from the operational dataset.

The confusion matrix shown in Fig. 6 indicates that the Random Forest classifier successfully distinguished the majority of healthy fibres, reflective connector faults, high-loss splice faults, and end reflections. However, moderate confusion was observed between certain fault categories exhibiting similar attenuation characteristics, particularly macrobending faults and fibre cuts.

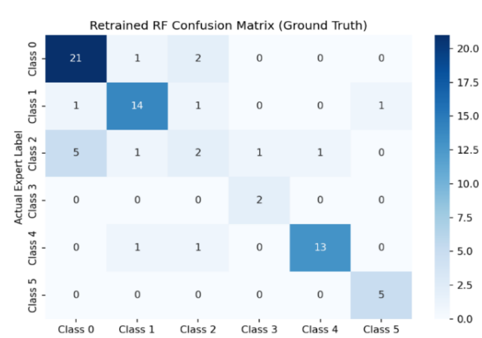

Fig. 6: Confusion Matrix of the Random Forest Classifier

Overall, the Random Forest achieved an accuracy of 78%, with a macro-averaged precision of 0.73, recall of 0.79, and F1-score of 0.75. These results demonstrate that conventional ensemble learning methods remain effective for OTDR fault diagnosis when informative features are available. Nevertheless, their performance depends heavily on manual feature engineering and may be limited in capturing complex signal characteristics directly from raw OTDR traces.

4.5 1D-CNN classification performance

The proposed 1D-CNN classifier was subsequently trained using the same expert-labelled dataset. Unlike the Random Forest model, the 1D-CNN learned hierarchical feature representations directly from standardized OTDR signals without requiring handcrafted feature extraction.

The confusion matrix presented in Figure 7 shows that the network achieved excellent recognition of healthy fibres, reflective connector faults, high-loss splice faults, and end reflections. The remaining classification errors were primarily associated with macrobending faults, which exhibited waveform characteristics similar to those of other attenuation-related events.

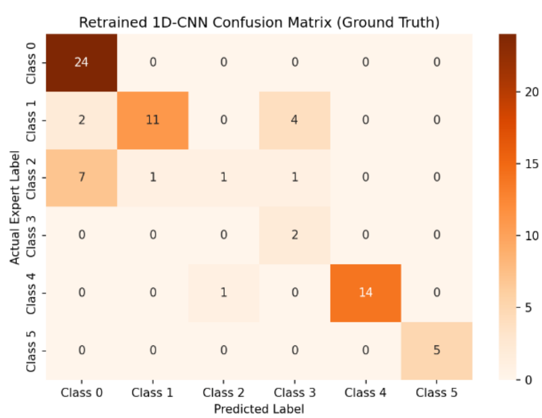

Fig. 7: Confusion matrix of the proposed 1-dimensional CNN

The detailed classification report indicates class-wise F1-scores of 0.84, 0.76, 0.17, 0.44, 0.97, and 1.00 for Classes 0–5, respectively. While the model demonstrated excellent performance for several fault categories, the relatively limited number of macrobending and fibre-cut samples constrained classification performance for these minority classes. Future work may therefore investigate synthetic data augmentation or generative learning approaches to improve recognition of underrepresented fault types.

4.6 Comparative performance evaluation

A quantitative comparison of the two supervised classifiers is presented in Table 4.

Table 4: Performance Comparison of the Random Forest and 1D-CNN Classifiers

Metric	Random Forest	Proposed 1D-CNN
Accuracy	0.78	0.78
Macro Precision	0.73	0.74
Macro Recall	0.79	0.78
Macro F1-score	0.75	0.70
Weighted Precision	0.76	0.80
Weighted Recall	0.78	0.78
Weighted F1-score	0.77	0.76

The results indicate that both classifiers achieved identical overall classification accuracy. However, their behavior differed across the evaluated performance metrics. The Random Forest achieved slightly higher macro recall and macro F1-score, suggesting more balanced performance across all fault categories. Conversely, the proposed 1D-CNN obtained higher weighted precision and weighted recall, reflecting superior performance on the more frequently occurring operational fault classes.

Although the numerical differences between the two classifiers are relatively small, the proposed 1D-CNN offers an important practical advantage by learning discriminative representations directly from OTDR waveforms without relying on manually engineered features. This characteristic enhances scalability and facilitates deployment in intelligent fibre monitoring systems where diverse fault signatures may evolve over time.

5. DISCUSSION

The experimental findings demonstrate that the proposed hybrid artificial intelligence framework provides a practical approach to automated OTDR-based fault diagnosis by combining unsupervised anomaly detection, expert-guided ground-truth construction, and supervised multi-class classification. Rather than relying on a single learning algorithm, the framework separates the diagnostic process into complementary stages. The convolutional autoencoder is used to learn the characteristics of healthy OTDR measurements and identify traces that deviate from the learned representation, while the supervised classifiers subsequently distinguish among the identified fault categories. This staged architecture provides a logical structure for analyzing operational OTDR measurements, where healthy and faulty traces may occur together.

A major strength of the framework is the use of healthy OTDR measurements to establish the normal signal representation for anomaly detection. Training the convolutional autoencoder on healthy traces allows the model to learn the dominant characteristics of normal fibre behavior without requiring labelled examples of every possible fault. When a trace differs substantially from this learned representation, its reconstruction error provides an indication that the measurement may contain an abnormal event. This approach is particularly relevant to operational optical networks because it is unrealistic to assume that every possible fibre fault will be known and adequately represented in the training dataset. The anomaly-detection stage therefore provides an initial screening mechanism before detailed fault categorization.

The subsequent classification results demonstrate the complementary behavior of conventional machine learning and deep learning. The Random Forest and 1D-CNN classifiers both achieved an overall accuracy of 78%, although differences were observed in their class-level and averaged evaluation metrics. The 1D-CNN achieved higher weighted precision and weighted recall, suggesting that its learned hierarchical representations were effective in capturing discriminative characteristics directly from the standardized OTDR waveforms. Through successive convolutional operations, the model can identify local signal patterns and combine them into higher-level representations without depending entirely on manually designed features.

The Random Forest nevertheless remained a useful and competitive benchmark. Its slightly higher macro-averaged F1-score indicates comparatively balanced performance across the evaluated classes, despite its overall accuracy being identical to that of the 1D-CNN. This finding is important because it demonstrates that increasing model complexity does not automatically guarantee superior performance across every evaluation criterion. The effectiveness of a classifier depends on factors including class distribution, the number of available training examples, signal variability, and the quality of the extracted representations. Consequently, the results support the inclusion of classical machine-learning models as meaningful benchmarks rather than treating deep learning as inherently superior.

The quality of the ground-truth labels is another important consideration when interpreting these results. In this study, anomalous operational OTDR traces were examined and assigned to predefined fault categories using expert interpretation of the observed signal characteristics. The resulting labels were therefore not derived solely from simulated fault parameters or automatically generated class assignments. This is particularly relevant because operational OTDR traces can exhibit variations in attenuation, reflection, event location, and signal shape that may not be fully represented by simulated or laboratory-controlled measurements. Expert-guided annotation provides a physical basis for the classification targets and consequently strengthens the usefulness of the resulting dataset for supervised learning.

The six-class formulation adopted in this study also provides a structured representation of the principal diagnostic conditions considered in the investigation: healthy fibre, reflective connector, macrobend, fibre cut, high-loss splice, and end reflection. These categories represent physically meaningful events that can be associated with identifiable characteristics in OTDR traces. However, the classification results also indicate that the diagnostic problem remains challenging, particularly for classes represented by fewer observations. The available operational measurements do not provide perfectly balanced class distributions, and some fault categories contain substantially fewer examples than others. This imbalance can affect the ability of supervised models to learn representative decision boundaries for minority classes.

The results should therefore be interpreted in the context of the available operational dataset rather than as evidence that one learning paradigm is universally superior. The 1D-CNN provides an important advantage through automatic representation learning, whereas Random Forest offers a comparatively simpler and computationally efficient benchmark. The comparable overall accuracy obtained by the two approaches suggests that the quality and diversity of the underlying operational measurements may be at least as important as the choice of classifier. Increasing the quantity and diversity of operationally labelled OTDR measurements may consequently provide greater improvements in generalization than simply increasing model complexity.

Another important consideration is the distinction between anomaly detection and fault classification. These are related but different diagnostic tasks. Anomaly detection determines whether an OTDR measurement deviates from the learned representation of normal behavior, whereas multi-class classification attempts to determine the specific type of fault responsible for an abnormal trace. Treating these tasks separately provides greater flexibility because the anomaly detector does not need to anticipate every possible fault category. At the same time, the subsequent classifier can focus on a more restricted set of known diagnostic classes. This separation is consistent with the practical structure of fibre monitoring, where an abnormal link may first be identified and subsequently examined to determine the likely cause.

Despite the promising results, several limitations should be acknowledged. First, the operational measurements were obtained from a particular monitoring environment, and therefore the observed signal characteristics may not represent every optical network configuration. Second, the available dataset contains unequal numbers of observations across fault categories, which can influence class-specific performance. Third, the evaluation was performed offline; consequently, the present study does not establish the real-time computational performance of the complete framework when integrated directly with an operational network-monitoring platform. Finally, although expert-guided labelling provides a stronger basis for ground truth than automatically generated labels, future studies could further strengthen the annotation process through independent assessment by multiple experts and formal inter-rater agreement analysis.

Overall, the findings indicate that reliable OTDR fault diagnosis depends on the interaction between data quality, ground-truth reliability, anomaly detection, and classifier design. The results do not suggest that deep learning should simply replace conventional machine learning. Instead, they demonstrate the value of combining complementary approaches within a structured diagnostic pipeline and, importantly, of evaluating those approaches using operational measurements with expert-derived labels.

6. PRACTICAL IMPLICATIONS AND FUTURE DIRECTIONS

The findings have several implications for practical optical fibre network monitoring. First, the anomaly-detection stage provides a mechanism for automatically screening large collections of OTDR measurements and identifying traces that warrant further examination. In a large operational network, this could reduce the number of measurements requiring direct manual inspection and allow maintenance personnel to concentrate their attention on potentially abnormal fibre links.

Second, automated multi-class classification provides an opportunity to support maintenance decision-making after an abnormal trace has been identified. Rather than merely indicating that a measurement differs from normal behavior, the classification stage attempts to associate the abnormal trace with a specific diagnostic category. Such information could assist maintenance personnel in prioritizing investigations and selecting appropriate corrective actions. However, the present results should be interpreted as demonstrating decision-support potential, rather than claiming complete autonomous maintenance capability.

The expert-guided ground-truth methodology also has practical significance beyond the specific classifiers evaluated in this study. A documented annotation procedure provides a basis for constructing additional operational datasets as new OTDR measurements become available. Future datasets can use the same class definitions and diagnostic criteria, thereby improving consistency between datasets and facilitating more meaningful comparisons between machine-learning approaches.

The proposed framework can also be extended as the diversity of operational measurements increases. Additional data from different fibre routes, network configurations, manufacturers, wavelengths, measurement settings, and environmental conditions could be incorporated to evaluate the generalization of the models across heterogeneous network environments. Increasing the number of observations for underrepresented fault categories would also provide an opportunity to investigate whether the classification performance of minority classes improves with additional operational examples.

Future research should additionally investigate independent multi-expert annotation and inter-rater agreement. Although expert-guided labelling provides an important improvement over automatically generated labels, the reliability of a ground-truth dataset can be assessed more rigorously when multiple qualified experts independently interpret the same traces. Disagreements can then be examined, resolved using predefined criteria, and documented as part of the annotation protocol. This would provide an additional measure of confidence in the resulting ground truth.

Another important direction is the development of online or near-real-time implementations. The current study evaluates the framework using previously acquired operational OTDR measurements. Future work could integrate the anomaly detector and classifier with automated OTDR acquisition systems so that new measurements can be analyzed as they are generated. Such an implementation would allow the computational latency, memory requirements, and stability of the framework to be assessed under continuous monitoring conditions.

Finally, future investigations could examine more advanced representation-learning approaches, including attention-based architectures, transformer models, transfer learning, and continual-learning strategies. These methods could be evaluated against the Random Forest and 1D-CNN benchmarks using expanded operational datasets. Importantly, however, model development should remain accompanied by careful ground-truth construction. Increasing architectural complexity without improving the quality and diversity of the underlying operational data may not produce corresponding improvements in diagnostic reliability.

The overall implication is therefore that intelligent OTDR monitoring should be viewed as a combination of reliable data acquisition, trustworthy ground-truth construction, anomaly screening, and appropriate model selection. The present framework provides a foundation for this approach by bringing these components together and demonstrating their application to operational OTDR measurements.

7. CONCLUSION

This paper presented a hybrid artificial intelligence framework for automated OTDR-based fault detection and multi-class classification in optical fibre networks. The proposed methodology integrates a convolutional autoencoder for unsupervised anomaly detection, expert-guided ground-truth labelling, a Random Forest benchmark classifier, and a one-dimensional convolutional neural network for supervised fault classification. By combining these complementary techniques, the framework provides an end-to-end diagnostic approach capable of identifying abnormal OTDR traces and accurately classifying multiple fibre fault categories using operational network measurements.

The proposed framework was evaluated using 45 healthy OTDR traces for unsupervised training and 366 expert-labelled operational OTDR traces representing six common fibre fault classes. Experimental results demonstrated that both the Random Forest and the 1D-CNN achieved an overall classification accuracy of 78%, while the 1D-CNN exhibited superior weighted precision and weighted recall through its ability to learn hierarchical representations directly from OTDR waveforms. The convolutional autoencoder also proved effective as an intelligent screening mechanism by distinguishing healthy and abnormal fibre conditions based on reconstruction error, thereby reducing the need for exhaustive manual inspection.

A major contribution of this work is the integration of expert-derived ground-truth labelling with unsupervised anomaly detection and supervised multi-class classification using real operational OTDR data. Unlike many previous studies that rely primarily on simulated datasets or isolated machine learning techniques, the proposed framework demonstrates the practical benefits of combining multiple artificial intelligence approaches within a unified diagnostic system. This integrated methodology enhances the reliability, interpretability, and applicability of intelligent OTDR analysis for modern optical communication networks.

Future research will focus on extending the framework using larger and more diverse operational datasets, investigating transformer-based deep learning architectures and self-supervised learning techniques, and implementing the proposed methodology within real-time software-defined optical network management systems. Such developments have the potential to further improve predictive maintenance capabilities and contribute to the realization of autonomous optical communication infrastructures.

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