Expertise-Embedded Machine Learning for Enhanced Failure Management of Optical Modules in OTN

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Abstract: We propose an expertise-embedded approach for failure management of optical modules in OTN that incorporates expert decision-making logic into data-driven ML models, thereby enhancing inference capabilities. Empirical assessments reveal a marked performance enhancement in models post-embedding, particularly in few-shot failure scenarios.

1. Introduction

With the rapid growth of high-bandwidth services such as cloud computing, the Internet of Things (IoT), the Internet of Vehicles (IoV), and high-definition video, optical transport networks (OTNs) are playing an increasingly prominent role in modern communications [1]. Central to these OTNs are the optical modules, which serve as the backbone for transmitting vast amounts of data. As data traffic surges, ensuring the reliability of these optical modules becomes paramount. A failure in these modules can lead to data loss or even service interruption, incurring significant losses for enterprises and users. While machine learning (ML) technologies present promising solutions for the failure management of optical modules in OTN [2-5], they face several challenges. The diverse and intricate nature of failures in optical modules, ranging from hardware defects and software errors to physical damages, challenges the capacity of ML to capture the entire complexity. Moreover, ML methods, predominantly driven by historical data, face limitations in real-world OTNs where module failure data might be scarce. This scarcity often results in data imbalances, hindering effective model training.

In this context, the expertise of professionals experienced in OTN operations becomes invaluable. These experts, through years of hands-on experience, have a nuanced understanding of complex failure patterns in optical modules, insights that might escape conventional ML methods [6-9]. However, one of the pivotal challenges is the systematic acquisition and quantification of such rich expertise. Even though experts possess profound insights into diverse failure modalities, this knowledge often remains intangible and challenging to articulate. Moreover, having successfully captured and quantified this expertise, the subsequent challenge lies in effectively embedding or applying this knowledge within extant machine learning models, ensuring its broad applicability across various scenarios and tasks.

To address challenges encountered in failure management of OTN optical modules, we propose an expertise-embedded approach, enhancing downstream model performance by incorporating expert decision logic into the data. Expert decision-making is captured through tree-based models and embedded in the 'Expertise' feature, thereby imbuing the dataset with expert knowledge. This method is advantageous as it's effective in sparse fault scenarios and only relies on a few samples. Meanwhile, it offers broad compatibility at the data feature level, ensuring flexibility in model selection. We assessed the diagnostic performance of before and after expertise embedding in the data-driven model using real optical module data from the optical transmission network. The results indicate an average F1 score improvement of 0.1945 compared to the data-driven model.

2. Expertise-Embedded Approach for failure management of optical modules in OTN

Figure. 1 outlines the Expertise-Embedded Approach for OTN optical module failures. It begins with data collection, contrasts with traditional models, and details the two main stages: Expertise Capture and Embedding.

OTN, designed for efficient optical fiber multiplexing, comprises routing nodes with OTN boards. These boards house optical modules that transition between electrical and optical signals. Sensors in these modules track parameters such as power, temperature, and error rates. Periodic telemetry, depicted in Fig. 1(a), collects this performance data, which, when paired with fault tickets, facilitates sample annotation.

Fig. 1(b) highlights the distinction between the training processes of conventional and Expert-embedded models. By seamlessly fusing expert decision data at the data level, the approach both enhances the performance of downstream models and ensures broad compatibility, eliminating the need for architectural adjustments to existing models.

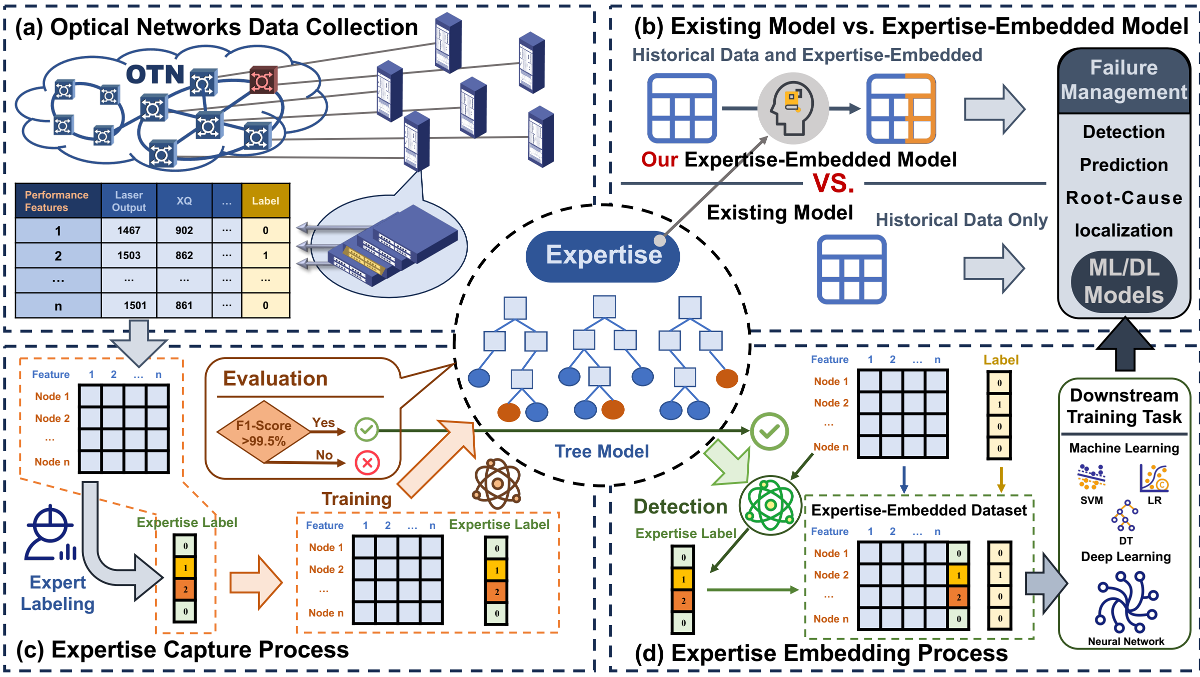

Fig. 1. Expertise-Embedded Approach for failure management of optical modules in OTN. (a) Optical Module Data Collection. (b) Existing Model vs. Expertise-Embedded Model. (c) Expertise Capture Process. (d) Expertise Embedding Process.

The Expertise Capture Process, depicted in Fig. 1(c), is the first phase of the Expertise-Embedded approach, aiming to encapsulate expert decision-making logic using a tree model. A dataset of 45,055 unlabeled entries was annotated by domain experts, uncovering 75 faults: 54 at Level 1 and 21 at Level 2. Given the inherent nature of expert judgment, which often resembles a combination of multi-threshold decisions, a decision tree model was deemed apt for emulating this logic. Post-training, the model achieved an F1-Score of 0.9712, indicating a satisfactory fit. This high score suggests that the decision tree model effectively encapsulates the expert's decision-making experience. Consequently, the expert decision logic was reverse-engineered from this trained model, resulting in a decision tree diagram, as presented in Fig. 2.

The Expertise Embedding Process, illustrated in Fig. 1(d), is the second phase. Utilizing the decision tree based on expert judgments, expert labels are inferred from dataset features. These labels are then added to the performance dataset as an additional feature, embedding expert knowledge. The resulting dataset, enriched with expert insights, serves as the basis for subsequent model training in downstream tasks.

3. Experimental Results and Analysis

The dataset, derived from real-world OTN boards and optical modules in the core network, was provided by our partner equipment manufacturer, as shown in Fig. 3(a). Comprising 6,885 samples, a mere 0.73% are identified

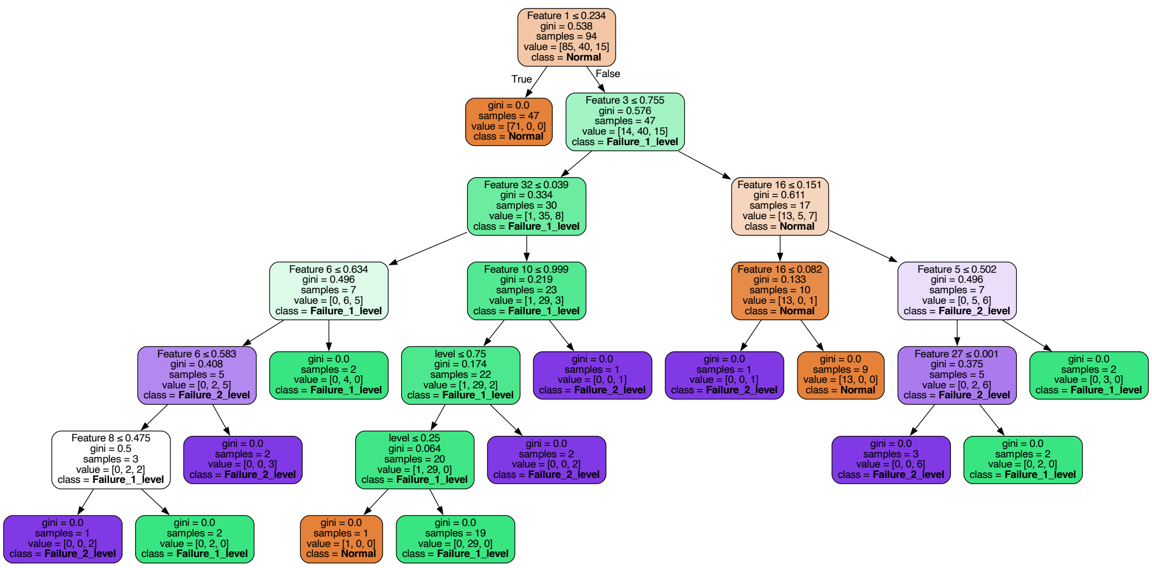

Fig. 2. Expertise Decision Logic Tree Diagram. (Features anonymized as Feature 1-32 and data appropriately normalized for privacy and security reasons)

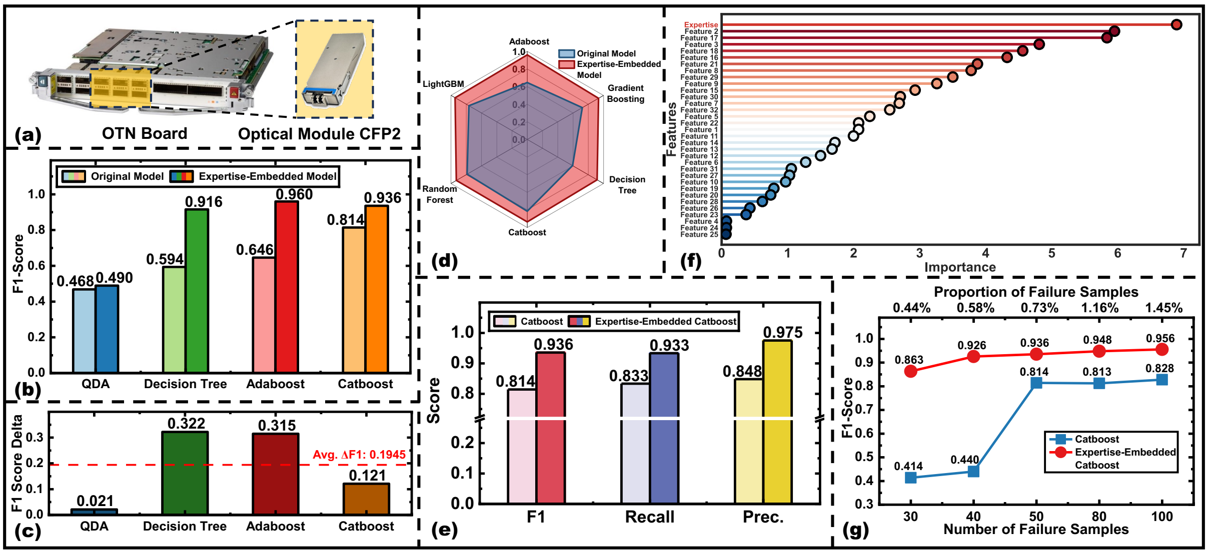

Fig. 3. (a) OTN Board and Optical Module. (b) Traditional vs. Expertise-Embedded Models' F1-score. (c) F1-Score Change with Expertise-Embedded for Four Models. (d) F1-Score Before and After Expertise-Embedded for Mainstream Models. (e) Catboost Metrics Before and After Expertise-Embedded. (f) Expertise-Embedded Catboost Feature Importance. (g) Impact of Failure Sample Variation on Model Performance Before and After Expertise-Embedded.

as failures. This data, split 8:2 for training and testing, includes features like real-time temperature, input optical power, and modulator parameters, etc.

To gauge the efficacy of the Expertise-Embedded approach, Fig. 3(b) contrasts the F1-scores of traditional and expertise-augmented models, with the latter consistently outperforming. This superiority is further quantified in Fig. 3(c), showing an average F1-score improvement of 0.1945. Fig. 3(d) extends this comparison to six mainstream models, all benefiting from the Expertise-Embedded approach.

For a more granular analysis, the Catboost model, a widely-adopted gradient boosting algorithm, was selected for comprehensive evaluation. A deeper dive into the Catboost model in Fig. 3(e) reveals marked improvements in key metrics when adopting the Expertise-Embedded approach. Fig. 3(f) showcases feature importance within the Catboost framework. Notably, the 'Expertise' feature emerges as a dominant contributor, underscoring its significant influence and the value of embedding domain expertise into ML models.

Addressing the real-world challenge of sparse failure data, Fig. 3(g) demonstrates the Expertise-Embedded approach's resilience in data imbalances. Even in extreme imbalances, the approach consistently outperforms the standard Catboost model, highlighting its potential in predictive modeling under challenging conditions.

4. Conclusion

We proposed an expertise-embedded approach tailored for optical modules in OTN, seamlessly integrating expert decision-making into ML models to bolster inference capabilities. We evaluate the diagnostic performance of this approach using real optical module data from the optical transmission network. The experimental results demonstrate a significant improvement in model performance after embedding expertise, particularly in few-shot failure scenarios. Additionally, feature importance visualizations highlight the crucial role played by the expertise feature in driving model efficacy.

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