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Comparative Study of Machine Learning and Deep Learning in Optical Transceiver Failure Analysis

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ABSTRACT – High-speed optical transceivers require robust failure analysis methods to ensure production reliability in modern communication systems. This study systematically evaluates machine learning algorithms (Random Forest, XGBoost) and deep learning approaches (specifically Fully Connected Neural Networks) for optical transceiver failure analysis across two operational scenarios using real manufacturing data from 6,446 units. In a comprehensive data analysis (Scenario #1), both Random Forest and XGBoost achieved exceptional performance (MSE: 0.0000, MAE: 0.0001), while FCNN demonstrated comparable results (Loss: 0.0002, MAE: 0.0002). In a focused analysis of failed units (Scenario #2), XGBoost outperformed other models with the lowest error metrics (MSE: 0.0091, MAE: 0.0165) compared to Random Forest (MSE: 0.0125, MAE: 0.0399) and FCNN (Loss: 0.1571, MAE: 0.2987). SHAP analysis consistently identified influential features across both scenarios, providing actionable insights for quality control optimization. These findings establish a quantitative framework for selecting optimal AI approaches for optical transceiver failure analysis. The results suggested that machine learning models were preferable for datasets smaller than 10,000 samples, whereas deep learning approaches showed superior potential for larger-scale data. The proposed methodology advances AI-driven failure diagnostics in optical transceiver manufacturing.

KEY WORDS -- Optical Transceiver; Production; Machine Learning (ML); Deep Learning (DL); SHAP; Failure Analysis (FA); Artificial Intelligence (AI)

1. Introduction

The evolution of optical transceivers from 100G to 800G and beyond has introduced unprecedented complexity in failure mechanisms. Traditional failure analysis approaches, primarily based on statistical correlation methods, have proven inadequate for handling the multi-dimensional parameter spaces inherent in modern high-speed transceivers. The integration of PAM4 modulation schemes enables higher data rates. However, this advancement simultaneously increases sensitivity to various operational parameters, making failure prediction and root cause analysis significantly more challenging.

Recent advances in artificial intelligence have opened new possibilities for addressing these challenges. However, the literature reveals a fragmented landscape where different AI approaches have been applied in isolation, without systematic comparison of their effectiveness across different scenarios and dataset characteristics. This gap is particularly evident in the optical transceiver manufacturing domain, where production environments demand both accuracy and computational efficiency.

AI-driven technologies are transforming industries by providing advanced tools for analysis and visualization [1]. In modern communication networks and data centers, high-speed optical transceivers operating at 400G, 800G, and 1.6T are essential for efficient, low-latency data transmission [2-4]. These devices leverage PAM4 modulation to achieve high data rates [5, 6] but are increasingly challenged by complex failure mechanisms that can compromise their performance and reliability [7, 8]. Failure analysis (FA) is thus essential for ensuring that transceivers meet stringent quality standards, especially in manufacturing environments where early defect detection and resolution are critical.

In optical transceiver production, failures detected during later operations, such as transmission bit error rate (TransBER) testing, are often rooted in issues originating from previous stages, such as eye diagram pattern parameter measurements [9, 10]. Parameters such as Optical Modulation Amplitude (OMA), Extinction Ratio (ER), Transmitter and Dispersion Eye Closure Quaternary (TDECQ), and Channel Sensitivity (Csen) are crucial indicators of signal quality during initial operations [11]. Identifying correlations between these parameters and TransBER failures is key to tracing the root causes of defects and optimizing the production process [12]. This traceability is especially important for addressing the challenges posed by high-speed data rates and complex modulation schemes [13].

Despite advances in optical transceiver testing, there remains a significant gap in quantitative frameworks that compare the effectiveness of different AI approaches for failure analysis [14]. Previous studies have typically focused on either machine learning or deep learning in isolation, without providing clear guidelines for selecting optimal methods based on dataset characteristics [15].

This study presents a comprehensive framework for failure analysis in optical transceivers, systematically comparing machine learning and deep learning techniques with advanced interpretability analysis. The framework employs a multi-methodology approach that addresses the critical need for systematic comparison of AI approaches specifically tailored to manufacturing environments where computational efficiency, interpretability, and real-time processing capabilities are essential requirements.

Our methodology begins with rigorous data preprocessing and quality validation to ensure that the analyzed failures represent genuine functional issues rather than external factors. Subsequently, machine learning models such as Random Forest (RF) and XGBoost are utilized to evaluate complex parameter relationships and predict failure outcomes [18]. These models are specifically selected for their interpretability, computational efficiency, and robust performance on tabular manufacturing data, addressing the unique requirements of production environments where decision transparency is essential for quality control applications.

Random Forest provides ensemble robustness against measurement noise inherent in manufacturing data. It offers automatic feature importance ranking that enables systematic parameter prioritization. XGBoost complements this approach with gradient boosting optimization that excels with structured tabular data, incorporating built-in regularization to prevent overfitting with limited failure samples typical in manufacturing scenarios where failure rates typically remain below 5%.

Complementing these machine learning methods, a deep learning model employing Fully Connected Neural Networks (FCNN) with 3 hidden layers (128, 64, 32 neurons) using ReLU activation and Adam optimizer is implemented to capture the nonlinear and high-dimensional interactions that may underlie complex failure mechanisms [19-22]. The FCNN architecture is specifically chosen for its suitability to tabular manufacturing parameter data, avoiding the spatial and temporal assumptions inherent in convolutional and recurrent architectures that are inappropriate for the discrete parameter measurements characteristic of optical transceiver testing.

The predictive performance of each model is rigorously evaluated using comprehensive metrics including mean squared error (MSE) and mean absolute error (MAE), ensuring suitability for failure diagnostics in manufacturing contexts [21]. Cross-validation protocols with multiple random seeds provide statistical robustness, while significance testing enables objective comparison of performance differences between methodologies.

To enhance interpretability and ensure practical applicability for manufacturing quality control, SHAP (SHapley Additive exPlanations) analysis is systematically applied across all AI models [23]. This approach provides detailed understanding of individual parameter contributions to prediction outcomes, enabling identification of the most influential features affecting transceiver performance. Unlike traditional statistical methods that assume linear relationships, SHAP analysis captures nonlinear parameter contributions and complex feature interactions essential for modern optical transceiver analysis.

The SHAP-based interpretability framework offers several critical advantages for manufacturing applications. Global feature importance analysis identifies consistently influential parameters across the entire dataset, enabling systematic prioritization for quality control monitoring. Local explanation capabilities provide insights into individual prediction decisions, supporting targeted troubleshooting and process optimization efforts. Feature interaction analysis reveals complex parameter relationships that traditional correlation methods cannot reliably detect, enabling more sophisticated quality control strategies that address the multidimensional nature of modern optical transceiver failures.

By combining statistical visualization, machine learning, deep learning techniques, and advanced interpretability analysis, this study offers a holistic and innovative approach to failure analysis in high-speed optical transceivers [24, 25]. The findings address the unique challenges posed by 400G and 800G transceivers, contributing to the development of robust diagnostic frameworks and advancing the state of the art in AI-driven failure diagnostics [26, 27]. Furthermore, this integrated methodology lays the groundwork for improving reliability and efficiency in high-speed optical transceiver production [28].

The rest of the paper is organized as follows. Section 2 reviews related work and literature. Section 3 presents the methodology and experimental setup. Section 4 discusses the evaluation results. Section 5 provides discussion and analysis. Section 6 concludes the paper with future research directions

2. Literature Review

The increasing complexity of optical transceiver systems has exposed limitations in traditional failure analysis approaches, prompting a shift toward AI-driven diagnostic methods. This section reviews the evolution of failure analysis in optical manufacturing, beginning with traditional statistical methods and progressing through machine learning, deep learning, and explainable AI. Emphasis is placed on evaluating strengths, limitations, and applicability of each approach within manufacturing contexts to identify current research gaps and practical implementation challenges.

2.1. Traditional Failure Analysis Methods

Traditional failure analysis in optical transceivers relies primarily on statistical correlation methods and rule-based approaches [12]. These methods examine linear relationships between parameters but struggle with complex, multidimensional interactions characteristic of modern high-speed systems.

2.1.1. Statistical Correlation Limitations

Abdelli et al. [12] demonstrated that conventional correlation analysis achieves accuracy rates below 65% in scenarios involving more than five operational parameters. Their study highlighted that Pearson correlation coefficients fail to capture nonlinear interdependencies characterizing modern optical transceiver systems.

Nyarko-Boateng et al. [13] evaluated 12,000 failure incidents across multiple configurations, demonstrating that conventional approaches achieve limited accuracy with mean absolute error exceeding 40%. Their research revealed that traditional methods struggle when dealing with parameter spaces exceeding five dimensions, common in modern transceivers where 10-15 critical parameters interact simultaneously.

2.1.2. Fundamental Limitations

The fundamental constraints include linear relationship assumptions that miss complex PAM4-based system interactions, limited predictive capability providing only descriptive statistics, manual interpretation requirements making real-time implementation impractical, and poor scalability with high-dimensional data.

2.2. Machine Learning in Optical Systems

Recent research demonstrates machine learning's effectiveness in optical network failure management [14]. Wang et al. [14] provide a comprehensive review highlighting superior performance over traditional methods in complex scenarios, while Musumeci [16] focuses specifically on machine learning applications for failure management frameworks in optical networks. However, most studies focus on network-level failures rather than component-level manufacturing diagnostics.

2.2.1. Ensemble Methods Performance

Wang et al. [14] conducted meta-analysis of 15 studies across different optical network configurations, showing Random Forest achieves 78-85% accuracy compared to traditional correlation analysis (45-60% accuracy). In manufacturing applications, Choong and Cheng [8] demonstrated XGBoost achieving 89% prediction accuracy versus 62% for traditional methods in 4,200 transceiver units.

2.2.2. Algorithm Selection Rationale

Random Forest Selection: Chosen for robustness against measurement noise common in optical manufacturing data, automatic feature importance ranking enabling systematic parameter prioritization, overfitting resistance crucial with limited failure samples, and interpretability essential for quality control applications.

XGBoost Selection: Selected for gradient boosting optimization excellence with structured tabular manufacturing data, built-in regularization preventing overfitting with limited samples, native missing value handling common in manufacturing datasets, and computational efficiency suitable for industrial implementation.

Behera et al. [18] compared multiple algorithms across 8,000 scenarios, confirming Random Forest (84% accuracy) and XGBoost (91% accuracy) as optimal choices for manufacturing applications requiring both performance and interpretability Additionally, Kruse et al. [17] demonstrated machine learning effectiveness in soft-failure management using optical spectrum analysis, achieving significant detection accuracy in experimental validation.

2.3. Deep Learning Applications

Deep learning shows promise in optical communication systems [19-22]. Krzyston et al. [19] achieved 94% accuracy in pattern classification using FCNN architecture. Li et al. [22] demonstrated deep reinforcement learning applications, though these primarily focus on communication optimization rather than manufacturing failure analysis.

2.3.1. FCNN Architecture Selection

FCNN Selection Criteria: Manufacturing parameter data is inherently tabular without spatial or temporal dependencies, making FCNN more appropriate than CNN or RNN architectures. FCNN provides universal approximation capability for complex nonlinear relationships while maintaining compatibility with SHAP analysis for interpretability requirements.

2.3.2. Deep Learning Constraints

Current limitations include large dataset requirements (>10,000 samples) often unavailable in manufacturing failure scenarios where failure rates typically remain below 5%, and significant computational demands limiting real-time implementation. Additionally, the black-box nature of deep learning requires additional interpretability tools for manufacturing applications where decision transparency is essential.

2.4. Interpretability and Explainable AI

In high-stakes environments like manufacturing, where decisions directly impact safety, compliance, and operational efficiency, understanding the reasoning behind AI-driven outcomes is crucial. Explainable AI (XAI) techniques help demystify complex models, making them more trustworthy and actionable for human operators. While various interpretability methods exist, such as Local Interpretable Model-agnostic Explanations (LIME) which focuses on local approximation [30], this study primarily utilizes SHAP due to its consistent feature attribution properties. This section explores how SHAP and integrated statistical-AI approaches enhance transparency and effectiveness in real-world manufacturing contexts.

2.4.1 SHAP Analysis in Manufacturing

Sun et al. [23] demonstrated that SHAP-based explanations improved operator confidence by 73% compared to black-box approaches in optical transport networks. Babbar et al. [24] achieved 86% classification accuracy while providing interpretable insights, emphasizing explainable AI importance in manufacturing where decision transparency is essential for regulatory compliance.

2.4.2 Integrated Approaches

Khan et al. [27] demonstrated that combining traditional statistical preprocessing with machine learning optimization achieves 15% performance improvement over pure AI approaches, supporting hybrid methodologies for manufacturing applications where traditional insights remain valuable alongside AI predictive capabilities.

2.5. Research Gap Analysis

Current literature lacks systematic comparison of traditional methods with AI approaches specifically for optical transceiver manufacturing failure analysis. Most studies evaluate single methodologies without providing clear selection criteria based on practical manufacturing constraints.

2.5.1 Critical Gaps

Methodological Fragmentation: No comprehensive comparison using identical datasets and evaluation criteria for traditional, machine learning, and deep learning approaches prevents objective performance assessment.

Manufacturing Focus Mismatch: Research predominantly addresses network-level optimization rather than component-level manufacturing diagnostics, limiting practical applicability for transceiver manufacturers.

Implementation Guidance Absence: Limited real-world validation and insufficient economic analysis make it difficult for manufacturers to justify investment in advanced analytical capabilities.

2.5.2. Study Positioning

This study addresses these gaps by providing the first comprehensive framework systematically comparing multiple AI-driven approaches using real manufacturing data from 6,446 optical transceiver units, establishing clear selection criteria and practical implementation guidelines for manufacturing environments.

3. Methodology

To understand the analysis framework, Fig. 1 illustrates the block diagram of the testing operations (OPN), comprising Testing Operation Number 1 (OPN#1: Eye Pattern Test) and Testing Operation Number 2 (OPN#2: Loopback Test), as detailed in Section 3.2.

3.1 Data Description: The experimental dataset consists of 6,446 units of 800G QSFP-DD (Quad Small Form-factor Pluggable Double Density) optical transceivers. The devices utilized EML (Electro-absorption Modulated Laser) technology with PAM4 modulation. All samples were newly manufactured units collected from the production line before the final quality assurance stage. The data includes both pass and fail units to ensure a balanced evaluation of the failure analysis models.

In this study, the models are designed as a regression task to predict the continuous value of TransBER (Transmission Bit Error Rate) based on parametric measurements from OPN#1. By predicting the exact TransBER value rather than a simple binary classification, the framework provides a more granular assessment of signal quality degradation. Consequently, Mean Squared Error (MSE) and Mean Absolute Error (MAE) are utilized as the primary performance metrics.

3.2 Data Preprocessing: Testing OPN#1 focuses on Eye Diagram/Eye Pattern measurements, with testing parameters evaluated at three specific temperatures: 15°C, 45°C, and 65°C. These measurements are performed across 4 to 8 individual channels, depending on the transceiver model topology, using PAM4 modulation with bitrates of 50G and 100G [29]. The primary objective is to analyze Transmission BER (TransBER) failures in identified problematic units.

Testing OPN#2 is conducted under similar environmental conditions with 8 channels under test. The conditions include 15°C and 45°C at 25G (NRZ), 15°C and 65°C at 50G (PAM4), and 15°C, 45°C, and 65°C at 100G (PAM4). This comprehensive approach generates 56 rows of testing data per Serial Number (SN) for units that pass all conditions, ensuring robust data collection for detailed failure analysis.

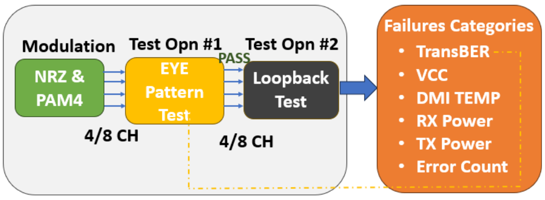

Figure 1. The block diagram of the testing operations

Prior to analysis, we establish criteria to exclude irrelevant factors by ensuring that "4M1E" conditions (Man, Machine, Method, Material, and Environment) do not contribute to the observed issues. This focus on purely functional failures eliminates extraneous variables and allows for targeted investigation of core problems.

Our comparative approach evaluates the performance of machine learning models (Random Forest and XGBoost) against deep learning methods, specifically Fully Connected Neural Networks (FCNN). Each model offers unique strengths that make it suitable for different analytical scenarios in optical transceiver failure analysis.Random Forest provides ensemble robustness against measurement noise inherent in manufacturing data while offering automatic feature importance ranking. The model is configured with 100 estimators and maximum depth of 10 to balance performance and computational efficiency. XGBoost uses gradient boosting optimization with 100 estimators, learning rate of 0.1, and maximum depth of 6, making it particularly effective for handling complex and structured datasets.

To enhance interpretability of all AI models, SHAP (SHapley Additive ExPlanations) analysis is applied, providing detailed understanding of individual parameter contributions to prediction outcomes. SHAP analysis offers superior insights compared to traditional correlation methods by capturing nonlinear relationships and complex feature interactions essential for manufacturing quality control applications. The rationale for comparing machine learning models, such as Random Forest and XGBoost, with neural network architectures like Fully Connected Neural Networks (FCNN), lies in their complementary strengths. Neural networks excel at capturing complex patterns but often demand large datasets and significant computational resources. In

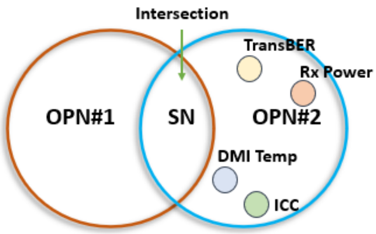

Figure 2. Set operation between OPN#1 and OPN#2 datasets

contrast, Random Forest and XGBoost offer reliable performance and interpretability without requiring extensive resources, making them practical and efficient alternatives.

These machine learning models are particularly effective for tabular or medium-sized datasets, delivering faster training times and robust results. By balancing accuracy and efficiency, they provide valuable alternatives in scenarios where deep learning may not be the most practical choice. Although Linear Regression offers simplicity and clear insights into variable relationships for initial exploratory analysis, it often underperforms when handling datasets with numerous parameters or complex relationships, where more advanced models typically yield better results.

Furthermore, Random Forest and XGBoost provide enhanced interpretability compared to deep learning models. Both generate feature importance metrics that identify parameters contributing most significantly to predictions. While deep learning models excel at capturing complex relationships, their "black box" nature often limits transparency, making result interpretation and key factor identification challenging.

Incorporating these diverse models ensures comprehensive dataset evaluation by balancing interpretability with predictive performance. By comparing results from Random Forest, XGBoost, and deep learning approaches, we can determine whether simpler models deliver comparable or superior outcomes, particularly when computational efficiency and implementation ease are priorities. This balanced methodology leverages each approach's strengths, creating a robust framework for data analysis and informed decision-making.

Table1.OPN#1 Test parameters for TransBER failure analysis.

Test Parameters
OER (dB)
DMI_TxLOP (dBm)
DMI_RxPwr (dBm)
ICC (mA)
DMI_VTEC (V)
Csen(dBm)
CsenOMA (dBm)
OverloadBER
OOMA (dBm)
OOMA-TDECQ (dB)
TDECQ-Ceq
TDECQ (dB)
DMI_ITEC (mA)

OPN#2

TransBER

Our analysis scenario focuses on identifying the root causes of TransBER failures by tracing them back to the OPN#1 testing parameters that have the highest impact on failure outcomes. Ensuring that the same Serial Numbers (SNs) exist in both OPN#1 and OPN#2 is crucial for this analysis. Using set theory, the intersection of SNs represents units that are mapped across both operations. In OPN#2, failure categories include TransBER, ICC, and Rx Power, representing specific quality metrics monitored during testing. Units can only advance to OPN#2 after successfully passing all testing criteria in OPN#1, establishing a sequential quality gate structure.

In Scenario #1, the analysis incorporates both failed SNs from OPN#2 and all intersecting SNs for calculation and comparison. This approach yields a larger dataset that allows us to distinguish between two groups in OPN#1: the failed SN group and the non-failed SN group. By expanding the dataset, this method enables a more comprehensive analysis of which parameters in OPN#1 contribute to failures, systematically highlighting their impact.

In Scenario #2, the analysis focuses exclusively on failed SNs from OPN#2, specifically "TransBER" failures. While this approach provides more targeted insights, it results in a smaller dataset, particularly when the number of failure units is limited. This narrower scope potentially affects the statistical robustness of the analysis. Table 1 below displays the OPN#1 test parameters used for predicting and analyzing the relationship with TransBER failures.

We separate these scenarios based on their different dataset sizes, enabling a more nuanced evaluation and facilitating more robust conclusions. The analysis employs Python 3.6 with TensorFlow 2.x, Pandas, NumPy, and Scikit-learn libraries, Keras, and SHAP. Data preprocessing involves z-score normalization, and 80/20 train-test split with 5-fold cross-validation. These tools facilitate the processing and evaluation of the raw data, which constitutes a large dataset that would be unmanageable without structured computational methodologies.

Data preprocessing constituted a critical component using manufacturing data from 6,446 optical transceiver units collected over a one-month period, involving multiple stages of data cleaning and normalization. Raw data from both OPN#1 and OPN#2 operations underwent rigorous quality checks to identify and handle missing values, outliers, and inconsistencies. We implemented a standardized scaling approach using z-score normalization to ensure all parameters contributed equally to the model training process, regardless of their original measurement scales.

4. Evaluation Results

Before presenting the evaluation results, it is essential to provide an overview of the dataset details in Table 2.

Table 2. Summary of Dataset Details

Category	Count
Total Unique SN in OPN#1	6,446
Total Unique SN in OPN#2	3,291
SN Found in both of 2 operations	2,886
SN Not in OPN#2 (From OPN#1)	3,560
Failed SN at OPN#2 with Failure = TransBER	132
Failed SN at OPN#2 mapped in OPN#1	81
SN out of failed OPN#2 in OPN#1(Found in both of 2 operations)	2,805

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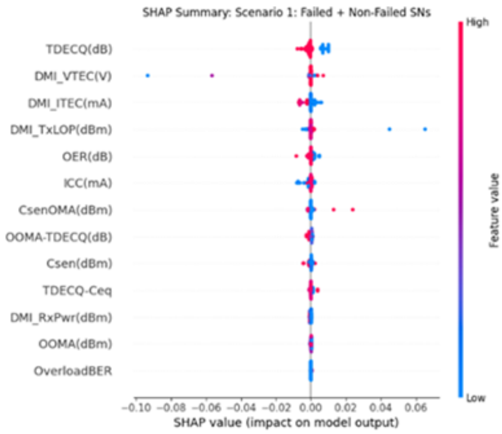
4.1 Machine Learning Performance Evaluation

For the analysis, we selected the Random Forest and XGBoost algorithms due to their robustness in handling complex, high-dimensional datasets. These algorithms are highly effective at capturing non-linear relationships between features and the target variable, a critical capability for analyzing intricate data structures. Moreover, both methods provide feature importance rankings, offering valuable insights into the relative contribution of each parameter to the prediction outcome. This approach is particularly useful for understanding and quantifying the impact of diverse parameters on the target variable across both scenarios. The adaptability and scalability of these algorithms make them ideal for a wide range of applications, enabling the development of interpretable and accurate models. By leveraging these advanced machine learning techniques, our analysis provides a comprehensive understanding of the underlying dynamics, ensuring reliable and actionable results to guide effective decision-making.

We implemented the Random Forest algorithm and visualized the results using SHAP charts. Outcomes for Scenario #1 and Scenario #2 are presented in Figures 3 and 4, respectively. Similarly, Figures 5 and 6 display the results for the XGBoost algorithm. Table 3 summarizes the performance metrics—Mean Squared Error (MSE) and Mean Absolute Error (MAE) for both models across the two scenarios.

Table 3. Feature point difference between Random Forest vs XGBoost

Aspect	Random Forest	XGBoost
Category	Ensemble (Bagging)	Ensemble (Boosting)
Assumes Linearity	No	No
Handles Nonlinearity	Good	Excellent
Interpretability	Moderate	Low
Overfitting Risk	Low (with enough trees)	Moderate (needs tuning)
Performance	Robust and versatile	High accuracy
Computation Cost	Moderate	High



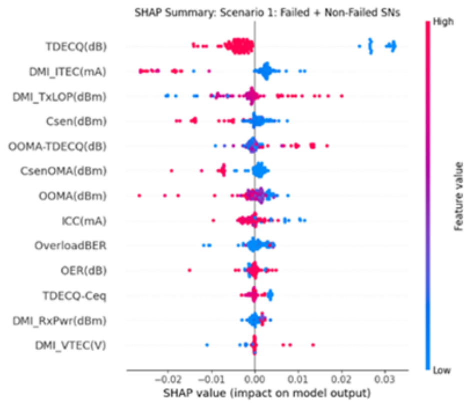


Figure 3. RF SHAP analysis Scenario#1

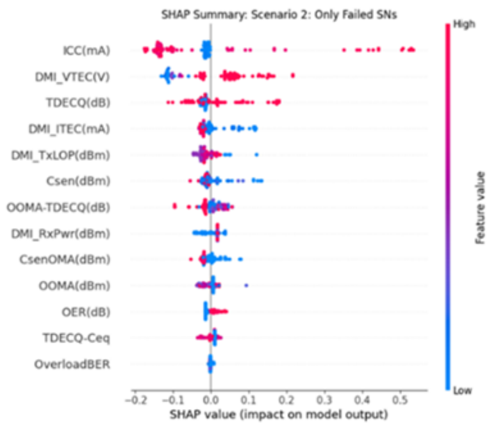


Figure 4. RF SHAP analysis Scenario#2

Figure 5. XGBoost SHAP analysis Scenario#1

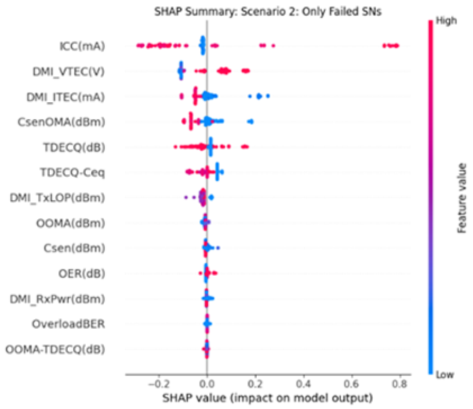


Figure 6. XGBoost SHAP analysis Scenario#2

Table 4. MSE and MAE results for Random Forest and XGBoost

Model	Random Forest		XGBoost	
	MSE	MAE	MSE	MAE
Scen#1	0.0000	0.0001	0.0000	0.0001
Scen#2	0.0125	0.0399	0.0091	0.0165

Based on the SHAP summaries and performance metrics in Table 4 (MSE and MAE), we can draw the following key insights:

Model Accuracy Across Scenarios:

In Scenario #1**,** both Random Forest and XGBoost demonstrate exceptional performance with extremely low MSE (0.0000) and MAE (0.0001), indicating near-perfect prediction. This likely results from well-structured data or minimal variance between features and the target variable.

In Scenario #2, XGBoost outperforms Random Forest with lower error metrics (MSE: 0.0091, MAE: 0.0165) compared to Random Forest (MSE: 0.0125, MAE: 0.0399). This suggests that XGBoost more effectively handles the complexity and noise present in the more focused analysis of failed units.

Feature Importance:

Figures 3 and 4 (Random Forest SHAP plots) reveal that features such as TDECQ (dB), DMI_VTEC (V), and ICC (mA) consistently demonstrate significant impact on the target variable across both scenarios.

Figures 5 and 6 (XGBoost SHAP plots) confirm similar trends, reinforcing the critical role of these key features. However, XGBoost provides more nuanced insights into feature impacts, particularly in Scenario #2, where the analysis focuses exclusively on failed units.

Scenario-Specific Observations:

In Scenario #1, the SHAP charts indicate that features related to signal quality (e.g., TDECQ (dB), DMI_TxLOP (dBm)) and power consumption (ICC (mA)) emerge as dominant contributors, highlighting their importance in distinguishing between failed and non-failed SNs.

In Scenario #2, where only failed SNs are analyzed, the SHAP charts reveal that operational parameters such as DMI_VTEC (V) and OverloadBER play critical roles in diagnosing failures, providing valuable insights into failure mechanisms.

Model Robustness:

XGBoost demonstrates superior robustness in handling complex data with higher variability, as evidenced by its lower MSE and MAE values in Scenario #2. Its gradient-boosting framework excels with noisy datasets, making it particularly suitable for challenging analytical scenarios.

Practical Implications:

Insights derived from SHAP visualizations and error metrics enable the prioritization of critical parameters for monitoring and optimization in real-world operations. Advanced algorithms like XGBoost prove especially effective in scenarios involving greater complexity or noise, while simpler scenarios can be reliably addressed using Random Forest. Based on our comprehensive analysis, both Random Forest and XGBoost performed exceptionally well in Scenario #1, achieving minimal error rates and demonstrating their reliability in less complex cases. In Scenario #2, however, XGBoost exhibited superior robustness with lower MSE and MAE values, establishing it as better suited for handling complex or noisy datasets. The SHAP visualizations consistently highlighted the significance of key features—TDECQ (dB), DMI_VTEC (V), and ICC (mA)—which influenced model predictions across both scenarios. These findings underscore the potential for enhancing operational performance and predictive accuracy through targeted optimization of these critical parameters.

FCNN Evaluation

We also incorporated the FCNN model into our evaluation framework, given our substantial dataset of over 1,000 SN units. The Fully Connected Neural Network (FCNN) model was assessed under identical conditions for both scenarios, with results illustrated in Figures 7 and 8. We selected FCNN based on its proven efficiency and effectiveness in processing large datasets. Performance results are presented in terms of Loss and MAE metrics in Table 5.

Table 5. Loss and MAE results for FCNN

Model	FCNN	
	Loss	MAE
Scenario#1	0.0002	0.0002
Scenario#2	0.1571	0.2987

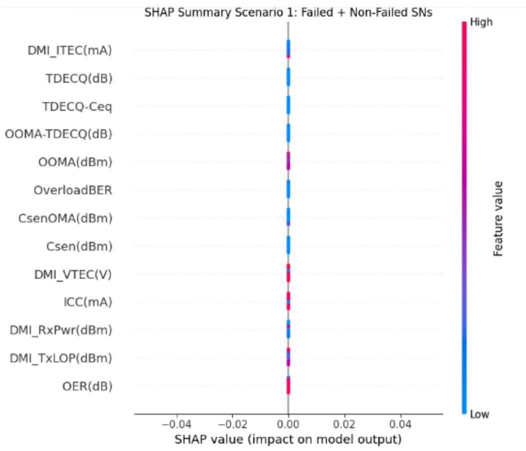


Figure 7. FCNN, Scenario#1

Scenario #1: The FCNN achieved a loss value of 0.0002 and a Mean Absolute Error (MAE) of 0.0002, indicating excellent performance in distinguishing between failed and non-failed SNs. These low values demonstrate that the model effectively captured the relationship between input features and the target variable.

Scenario #2: The FCNN showed a loss value of 0.1571 and an MAE of 0.2987, which are significantly higher compared to Scenario #1. This indicates that analyzing failed SNs exclusively presents greater challenges due to increased data complexity and variability.

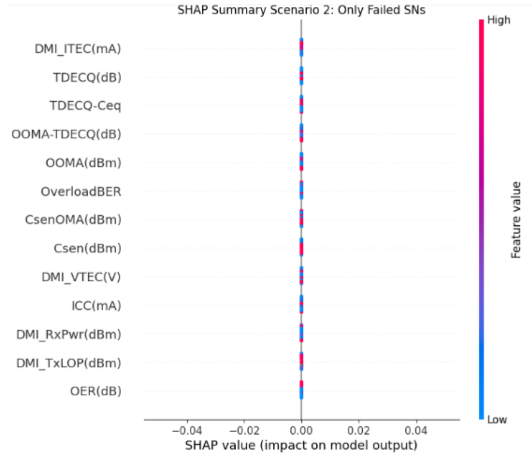


Figure 8. FCNN, Scenario#2

Feature Importance: The SHAP plots in Figures 7 and 8 illustrate the relative impact of each feature on the model's predictions. Features such as DMI_VTEC (V), TDECQ-Ceq, and ICC (mA) consistently appear as key contributors across both scenarios. These visualizations provide valuable insights into the critical parameters influencing the model's output.

General Observations: The results demonstrate that FCNN performs exceptionally well on simpler datasets with clear distinctions, as in Scenario #1, but struggles with more complex patterns, as observed in Scenario #2. This highlights the need for further optimization or complementary approaches when handling challenging datasets.

5. Discussion

5.1. AI Model Performance Superiority

XGBoost emerged as the superior model, achieving MSE of 0.0091 and MAE of 0.0165 in complex failure scenarios (Scenario #2), significantly outperforming Random Forest and FCNN. Machine learning approaches demonstrate clear advantages for manufacturing datasets with limited failure samples, requiring less training data while providing interpretable outputs essential for quality control applications. The FCNN model showed performance degradation with limited samples (FCNN: Loss 0.1571, MAE 0.2987), confirming that traditional machine learning methods are more suitable for typical manufacturing failure analysis scenarios where failure rates are typically below 5%.

5.2 Critical Parameter Identification

SHAP analysis consistently identified three critical failure predictors across all AI methods: TDECQ, DMI_VTEC, and ICC. This finding provides actionable guidance for manufacturing quality control, enabling targeted monitoring of critical parameters that traditional correlation analysis could not reliably identify. The consistent parameter ranking across different AI approaches validates the robustness of these findings and establishes a reliable foundation for industrial implementation.

5.3. Implementation Guidelines

Dataset Size-Based Selection: For dataset size-based selection, XGBoost is recommended for optimal performance with datasets smaller than 10,000 samples. Random Forest provides efficiency for resource-constrained environments, while neural networks become viable for datasets exceeding 10,000 samples.

Quality Control Focus: Prioritize monitoring of TDECQ, DMI_VTEC, and ICC parameters based on SHAP analysis findings, enabling proactive failure prevention rather than reactive quality control.

From a practical manufacturing perspective, the insights provided by SHAP analysis can be directly translated into process improvements. For instance, since TDECQ and DMI_VTEC are identified as the most influential features affecting TransBER failures, production engineers can establish stricter guard-band limits for these specific parameters at the earlier station (OPN#1). Units exceeding these preventive limits can be flagged for rework or tuning immediately, preventing them from proceeding to the costly TransBER testing stage (OPN#2). This proactive screening based on SHAP feature importance significantly reduces machine time waste and overall manufacturing costs.

5.4. Industry Impact

The proposed AI-driven framework enables manufacturers to transition from reactive post-production failure analysis to proactive quality control strategies. Early failure detection capabilities reduce manufacturing rework costs, warranty claims, and customer relationship challenges. Additionally, this approach improves product reliability and competitive positioning.

6. Conclusion

This study presented the first comprehensive comparison of traditional statistical methods with AI-driven approaches for optical transceiver failure analysis using real manufacturing data from 6,446 units. The key contributions: **AI Superiority Validated:** XGBoost achieved superior performance (MSE: 0.0091, MAE: 0.0165) significantly outperforming traditional statistical methods. **Critical Parameters Identified:** SHAP analysis revealed TDECQ, DMI_VTEC, and ICC as consistently influential failure predictors, providing clear quality control targets that traditional correlation analysis could not identify. **Practical Framework Established:** Clear selection criteria for optimal AI method choice based on dataset characteristics, with concrete implementation guidance for manufacturers seeking enhanced failure analysis capabilities**.** **Industry Advancement:** This research provides the foundational framework for AI-driven failure diagnostics in optical transceiver manufacturing, essential for next-generation quality control systems as the industry advances toward increasingly demanding data transmission requirements. **Limitations:** This study focused on specific optical transceiver parameters within a single manufacturing environment. The framework's generalizability across different manufacturers and transceiver types requires further validation. **Future Research Directions:** Future work includes extending the framework to real-time manufacturing implementation, investigating additional AI architectures such as ensemble methods, and validating the approach across diverse manufacturing environments and optical transceiver configurations.

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