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High-Accuracy Real-Time Soft Failure Detection in Optical Access Networks Using Hybrid Isolation Forest and One-Class SVM

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***Abstract** . This study presents a high-accuracy real-time soft failure detection framework for large-scale fiber-to-the-home(FTTH) optical access network using a hybrid ensemble of Isolation Forest and One-Class Support Vector Machine (OCVSM). The proposed model was trained and validated on a real-word multivariate performance dataset consisting of more than 1.8 million samples collected at 5-minute intervals from 50 Optical Line Terminals (OLTs) and over 3,000 Optical Network Terminals (ONTs) across a five-month period (June-October 2025). Ground-truth validation was performed using 111 confirmed network incidents in October 2025 affecting 12,990 customers. The hybrid ensemble achieved Precision 0.940, Recall 0.982, with an average detection delay of only 7.8 minutes-representing an 87.7% reduction compared to conventional manual response (63.5 minutes). The framework significantly outperforms traditional threesholding and recent ML-based methods while demonstrating practical deployability in live operational environments.*

***Keywords** : Ensemble Learning, FTTH, Isolation Forest, One-Class SVM, Optical Access Network.*

1. BACKGROUND

The explosive growth of fiber-to-the-home (FTTH) deployments has made optical access networks the backbone of modern broadband infrastructure, as outlined in a comprehensive survey of machine learning applications in optical networks (Musumeci et al., 2019). However, maintaining service availability above 99.9% in high-customer density environments remains a major challenge, where traditional methods often fail to address gradual soft failures (Rafique et al., 2020). Empirical data from a production FTTH network in October 2025 recorded 111 validated incidents resulting in a total downtime of 7,050 minutes and affecting 12,990 customers, highlighting the urgency of more sophisticated detection approaches.

Threshold-based monitoring still dominates current operational practices, but it is not reliable in detecting gradually developing, multivariate soft failures, such as macrobending, connector degradation, temperature-induced attenuation, and splitter aging, as discussed in a study on latency degradation (Wang et al., 2021). These anomalies rarely trigger simple univariate alarms, often being detected late and reducing customer satisfaction, highlighting the need for adaptive machine learning models.

Unsupervised machine learning enables automatic learning of normal patterns without costly anomaly labels, with algorithms like Isolation Forest excelling in high-dimensional data (Liu et al., 2008) and One-Class SVM robust for class separation (Schölkopf et al., 2001). Approaches like ensemble learning have been shown to provide performance improvements of

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up to 8–15% in 5G and optical networks, according to recent analyses (Kashyap et al., 2021; Zeng et al., 2020). However, the majority of studies still rely on simulated data, so this research fills the gap with a field-scale evaluation using real operational data.

2. THEORETICAL STUDY

Soft failure detection in optical networks has become a focus of intensive research due to the increasing demands for service level agreements. Surveys by Musumeci et al. (2019) and Rafique et al. (2020) confirmed that machine learning approaches improve accuracy by 20–30% compared to conventional thresholding methods. Isolation Forest (Liu et al., 2008) excels in high-dimensional anomaly detection, while One-Class SVM (Schölkopf et al., 2001) is robust in learning majority class boundaries. Hybrid ensembles have been shown to deliver 8–15% improvements in optical transport and 5G fronthaul networks (Kashyap et al., 2021; Zeng et al., 2020). However, most studies still use simulated or laboratory data. This study closes this gap with a field-scale evaluation using real operational data and verified incidents.

3. RESEARCH METHODS

This study uses an experimental design with multivariate performance data collected continuously every 5 minutes from 50 Huawei MA5800 OLT devices and more than 3,000 paired ONTs during June–October 2025, resulting in 1,836,720 samples. Monitored features include round-trip latency, jitter, packet loss ratio, downstream/upstream throughput, optical power (Tx/Rx), SNR, and module temperature.

Data processing included forward-fill and median interpolation for missing values, outlier filtering with IQR, Min-Max normalization [0,1], and pruning of highly correlated features (>0.87). The hybrid model consisted of Isolation Forest (300 trees, contamination=0.08, max_features=0.8) and One-Class SVM (RBF kernel, ν=0.09, γ=scale). Decision rule: anomaly if both models agree or Isolation Forest score >0.68. Real-time inference was achieved <50 ms per 1,000 samples using Scikit-learn 1.5.1.

4. RESULTS AND DISCUSSION

Incident Characteristics

During October 2025, 111 incidents were recorded with fluctuating daily distribution due to environmental factors and traffic loads .

Table 1. Characteristics of the October 2025 incident.

Parameter	**Mark**
Total incidents	111
Dominant type	PACKET_LOSS(42), LINK_DOWN(39), HIGH_LATENCY(30)
Severity level	High 34, Medium 41, Low 36
Customers affected	12. 990
Average duration	63.5
Most frequent nodes	NODE-001(16), NODE-005 (15), NODE-006 (13)

Table 2. Comparison of model performance.

Model	**Precision**	**Recall**	**Score**	**Delay**	**Detection Rate (%)**
Isolation forest	0.892	0.946	0.918	11.2	94.6
One-Class SVM	0.874	0.910	0.892	14.5	91.0
Hybrid Ensemble	**0.940**	**0.982**	**0.960**	**7.8**	**98.2**
Static Threshold	0.641	0.723	0.680	38.4	68.5

Results show the hybrid ensemble consistently excels in separating normal and anomalous conditions and provides the fastest response time, enabling proactive action before customers report an outage.

5. CONCLUSION AND SUGGESTIONS

A hybrid ensemble of Isolation Forest and One-Class SVM successfully improved real-time soft failure detection in a large-scale FTTH optical access network with an F1-score of 0.960 and an 87.7% reduction in detection delay (from 63.5 minutes to 7.8 minutes). A live implementation at the NOC demonstrated tangible operational benefits in the form of proactive detection of 98.2% of incidents. A limitation of this study is the reliance on data from a single OLT vendor. Future research is recommended to integrate the model with an automated ticketing system, extend it to 10G/25G-PON technologies, and utilize edge computing for lower latency.

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