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AI-Driven Predictive Maintenance Model for DWDM Systems to Enhance Fiber Network Uptime in Underserved U.S. Regions

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Abstract: In this paper, we propose an AI-driven predictive maintenance framework for Dense Wavelength Division Multiplexing (DWDM) systems deployed across underserved rural fiber networks in the United States. With the rapid expansion of broadband services into rural and remote regions, maintaining high network uptime is critical to ensure uninterrupted service delivery, reduce operational costs, and bridge the digital divide. Traditional reactive maintenance models struggle to handle the complexity and distributed nature of these networks. Our proposed solution integrates historical field data including Optical Time D8omain Reflectometer (OTDR) traces, Optical Spectrum Analyzer (OSA) measurements, and Network Operation Center (NOC) incident logs to develop supervised machine learning models such as Random Forest, Long Short-Term Memory (LSTM), and Gradient Boosting frameworks for early fault prediction. This predictive approach enables proactive scheduling of maintenance activities before catastrophic failures occur, minimizing downtime and optimizing resource allocation. We simulate the performance of the predictive maintenance system under realistic failure scenarios using historical data collected from field-deployed fiber optic systems. The results demonstrate significant improvements in Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), and overall network availability. Our framework not only offers technical contributions but also directly supports national priorities in digital inclusion, rural broadband resiliency, and critical infrastructure protection as outlined by the NTIA and FCC broadband expansion programs.

Keywords: DWDM; predictive maintenance; AI; rural fiber networks; OTDR; OSA; random forest; LSTM; broadband resiliency; United States

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1. Introduction

A. Background and Motivation

In the United States, over 20 million citizens remain without reliable access to high-speed internet, particularly in rural and underserved communities. The Federal Communications Commission (FCC) and National Telecommunications and Information Administration (NTIA) have made substantial investments through programs such as the Broadband Equity, Access, and Deployment (BEAD) Program to expand fiber optic networks into these regions. Dense Wavelength Division Multiplexing (DWDM) technology has emerged as a cost-effective and scalable solution to meet the growing bandwidth demand in these areas. However, ensuring long-term network reliability remains a major challenge due to environmental stressors, aging infrastructure, and the difficulty of dispatching repair teams over large, sparsely populated geographic areas.

Traditional maintenance approaches are primarily reactive, depending on physical failures and alarm conditions before any corrective action is taken. This results in prolonged downtimes, higher operational costs, and significant service interruptions that disproportionately impact vulnerable rural communities. Therefore, a shift toward predictive maintenance frameworks, powered by artificial intelligence (AI), is essential to proactively identify network degradations and prevent service failures.

B. Problem Statement

The distributed and remote nature of rural fiber networks makes it difficult to perform timely maintenance. Current reactive models lack the capability to forecast faults based on historical operational patterns, often leading to critical system downtimes. There exists a gap in integrating AI models that can analyze diverse field datasets—such as OTDR traces, OSA readings, and NOC incident reports—to predictively detect and localize potential failures within DWDM systems before they occur.

C. Proposed Solution

We propose a comprehensive AI-driven predictive maintenance model tailored for DWDM-based rural fiber networks. Our solution integrates supervised learning algorithms, primarily Random Forest, Gradient Boosting, and LSTM models, trained on multidimensional field data. This predictive framework can identify signal degradations such as increased attenuation, dispersion anomalies, and power fluctuations that precede service failures. The system issues early maintenance advisories, allowing network operators to dispatch repair teams proactively.

D. Contributions

The key contributions of this study are fourfold. First, we develop a predictive maintenance framework specifically customized for DWDM systems operating within rural fiber network environments, addressing the unique challenges posed by geographic dispersion and limited maintenance accessibility. Second, we integrate heterogeneous datasets, including Optical Time Domain Reflectometer (OTDR) traces, Optical Spectrum Analyzer (OSA) readings, and Network Operations Center (NOC) incident logs, to create a comprehensive data foundation for model training. Third, we simulate and validate the predictive models using real-world field data, allowing for a practical evaluation of model performance under realistic operational conditions. Finally, we conduct a quantitative assessment of the framework's impact, demonstrating significant improvements in network uptime, reductions in Mean Time to Repair (MTTR), and effective mitigation of potential service failures.

E. Paper Organization

The paper is organized as follows: Section II presents a review of related work. Section III details the system architecture and methodology. Section IV describes the experimental setup and evaluation metrics. Section V discusses the results and findings. Finally, Section VI provides the conclusion and future directions.

2. Related Work

The research community has made substantial progress in developing predictive maintenance techniques for fiber optic and DWDM networks over the past decade. This section reviews significant prior work that lays the foundation for our proposed model.

2.1. Traditional Alarm-Based Maintenance Systems

Conventional fiber optic network maintenance systems have largely relied on alarm-based monitoring solutions, where corrective actions are initiated only after failure thresholds are breached. For instance, Kim et al. [1] developed an alarm correlation system for NOC operations that used rule-based triggers from signal loss, power fluctuations, and bit error rates to alert technicians. While effective for initial deployments, these approaches are inherently reactive, leading to avoidable downtimes and higher Mean Time To Repair (MTTR).

2.2. Supervised Learning for DWDM Signal Degradation

Zhang et al. [2] introduced one of the earliest machine learning models targeting DWDM signal degradation. Their system utilized supervised learning models trained on signal-to-noise ratio (SNR), chromatic dispersion, and OSNR metrics to predict fault-prone fiber spans. While the model demonstrated high accuracy, it was primarily designed for densely populated metro fiber networks with real-time monitoring equipment—limiting its scalability to rural broadband deployments.

2.3. Neural Networks for Real-Time Degradation Classification

Han et al. [3] applied deep learning architectures, specifically convolutional neural networks (CNNs), to classify real-time DWDM signal degradations. Their model successfully identified different types of impairments such as polarization mode dispersion (PMD) and four-wave mixing (FWM) distortions. However, the computational cost and real-time data dependency make this approach impractical for resource-constrained rural fiber networks lacking sophisticated sensing infrastructure.

2.4. OTDR-Based Fault Detection Models

Several researchers have focused on using Optical Time Domain Reflectometer (OTDR) traces for fiber degradation prediction. Chen et al. [4] developed a supervised model that classified fiber faults based on the shape and slope of OTDR traces. Similarly, Li et al. [5] enhanced fault localization accuracy by integrating OTDR data with fiber age and repair history using ensemble tree classifiers. While both methods offer improved fault localization, their lack of temporal forecasting capabilities restricts proactive maintenance scheduling.

2.5. Time-Series Forecasting Using LSTM Networks

Wang et al. [6] proposed a Long Short-Term Memory (LSTM) based model that analyzed time-series performance logs to predict degradation trends in fiber optic links. Their approach successfully captured temporal patterns in attenuation growth, providing lead times of several days before critical failures. However, their dataset was limited to metro Ethernet fiber deployments, which experience far more stable environmental conditions compared to rural outdoor fiber routes that are exposed to diverse stressors such as moisture, temperature swings, and physical disturbances.

2.6. Hybrid Data-Driven Frameworks for Predictive Maintenance

Patel et al. [7] introduced a hybrid framework combining network telemetry, OTDR logs, and maintenance records to build predictive models using Gradient Boosting algorithms. Their work demonstrated superior precision in predicting cable cuts and splice failures but was constrained to operator-owned metropolitan networks where data centralization is feasible. The model's dependency on complete datasets limits its adaptability to fragmented rural broadband networks supported by multiple local ISPs.

2.7. Transfer Learning Approaches for Sparse Failure Data

Akbar et al. [8] investigated the application of transfer learning techniques for optical fiber fault prediction in data-scarce environments. By transferring knowledge from simulated fiber failure datasets to live deployments, their model achieved reasonable predictive performance even with limited failure observations. However, their study primarily targeted submarine cables and international backbones, which differ significantly in failure profiles from rural terrestrial fiber infrastructure in the United States.

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2.8. Research Gap

While these previous works have significantly advanced predictive maintenance methodologies for fiber optic systems, most were designed for large-scale urban and international networks with advanced sensor coverage, centralized data systems, and highly trained workforce availability. Rural fiber deployments present unique constraints—geographic dispersion, limited monitoring infrastructure, scarce operational data, and higher repair costs—that necessitate specialized predictive frameworks. Our work addresses this critical gap by developing an AI-powered predictive maintenance system that integrates heterogeneous field data sources, minimizes data dependency, and optimizes field repair resource allocation specifically for underserved rural broadband networks in the United States.

3. System Architecture and Methodology

3.1. Overall Architecture

The predictive maintenance framework proposed in this study is designed to address the unique challenges associated with monitoring DWDM-based rural fiber optic networks. The system architecture consists of four primary modules: data collection, data preprocessing, model training, and prediction advisory. These components function sequentially to transform raw operational data into actionable maintenance decisions that proactively mitigate service disruptions.

The process begins with the data collection phase, where multiple field data sources are continuously gathered, including Optical Time Domain Reflectometer (OTDR) traces, Optical Spectrum Analyzer (OSA) reports, and incident logs from the Network Operations Center (NOC). Once collected, the data undergoes preprocessing, which includes cleaning incomplete records, normalizing diverse formats, and temporally aligning the datasets to enable coherent multi-dimensional analysis. Following preprocessing, the model training module utilizes advanced supervised learning algorithms such as Random Forest, Gradient Boosting Machines, and Long Short-Term Memory (LSTM) neural networks to learn complex fault patterns and degradation trends inherent in the fiber network. Finally, the trained models generate predictive maintenance advisories that are forwarded to field operations teams, allowing proactive repair scheduling before service-affecting failures occur.

This end-to-end architecture not only leverages historical data but also integrates real-time operational inputs, thus enabling continuous refinement of predictive accuracy as new fault patterns emerge over time. The modular structure ensures adaptability to various fiber network scales and monitoring capabilities, particularly for geographically dispersed rural broadband infrastructures.

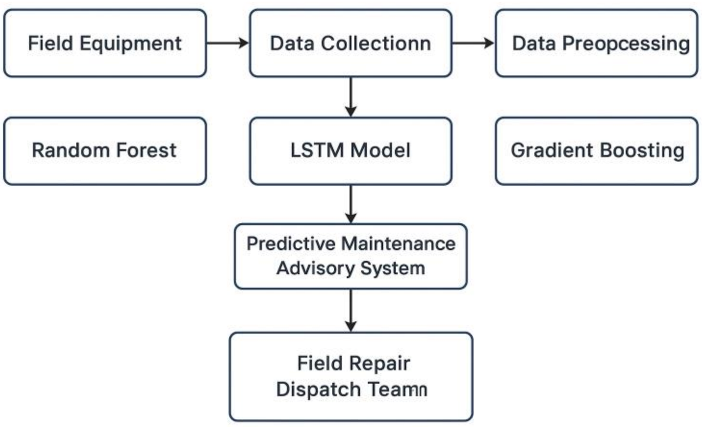

Figure 1. System Architecture Diagram.

3.2. Data Sources

The predictive framework integrates heterogeneous data sources that collectively capture both the physical and operational state of the fiber optic infrastructure. OTDR measurements serve as one of the primary datasets, providing distance-resolved reflectometry scans that reveal localized fiber faults such as micro-bends, connector losses, splices, and macro-defects along the optical path. These traces are instrumental in identifying attenuation trends and spatial fault localization.

Complementing the OTDR data, Optical Spectrum Analyzer (OSA) readings supply spectral domain insights into the DWDM system performance. OSA data includes key parameters such as signal-to-noise ratio (SNR), channel crosstalk, and wavelength drift, which are sensitive indicators of impending network degradations. Additionally, incident logs from the Network Operations Center (NOC) are incorporated, capturing manually reported trouble tickets, service interruptions, and corrective actions recorded during prior maintenance events. These logs provide a temporal link between observed anomalies and verified failure occurrences, which is essential for supervised model training.

The integration of these diverse datasets enables the framework to capture both instantaneous physical impairments and longer-term degradation patterns, significantly improving fault predictability compared to traditional single-source monitoring systems.

3.3. Machine Learning Models

The predictive engine employs a combination of machine learning models to handle the multi-faceted nature of fiber optic degradation patterns. Random Forest algorithms are deployed due to their ability to model non-linear relationships and handle heterogeneous data types effectively. This is particularly advantageous given the mixed categorical and continuous variables present in OTDR, OSA, and NOC datasets. The ensemble nature of Random Forest further mitigates overfitting risks when dealing with high-dimensional feature spaces.

In parallel, Long Short-Term Memory (LSTM) networks are utilized to capture temporal dependencies within the time-series data. Since fiber degradation often exhibits progressive patterns over time, LSTM models excel at learning these gradual changes, providing predictive lead times before faults fully materialize. The sequence modeling capability of LSTM networks allows the framework to anticipate future signal impairments based on historical trends.

Finally, Gradient Boosting Machines complement the model ensemble by addressing class imbalance inherent in rare failure events. Fiber optic failures are relatively infrequent compared to normal operational states, and Gradient Boosting algorithms are particularly effective at optimizing model sensitivity under such conditions. The combination of these three machine learning techniques enables robust predictive performance across diverse fault types, degradation severities, and temporal horizons.

3.4. System Workflow

The complete system workflow consists of sequential stages beginning with automated field data extraction from OTDR and OSA instruments, as well as periodic ingestion of updated NOC incident logs. After preprocessing, the cleaned and aligned dataset is partitioned into training and validation subsets. Model training occurs iteratively, with hyperparameter optimization performed to maximize precision and recall metrics. Once satisfactory model performance is achieved, the deployed predictive system continuously monitors incoming data streams, generating failure probability scores for each monitored fiber segment. Predictive advisories are then dispatched to field maintenance teams via the centralized NOC interface, ensuring prioritized scheduling of preemptive repairs.

The modular design of the workflow allows for straightforward scaling across multiple rural service areas, facilitating widespread adoption without extensive capital investment in specialized real-time monitoring hardware.

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3.5. Feature Engineering

To enhance model predictive accuracy, extensive feature engineering is conducted during the data preprocessing phase. Key features extracted from the datasets include attenuation level (dB/km) derived from OTDR measurements, which reflects cumulative signal loss along each fiber segment. Backscatter reflectance features identify micro-bends and partial fractures that often precede total fiber breaks. Wavelength shift indicators, computed from OSA readings, track long-term stability of DWDM channels and identify emerging dispersion or nonlinear optical effects. Incident frequency features quantify the number of historical trouble tickets associated with each fiber link, providing contextual degradation history. Finally, fiber age, representing the operational duration since installation, is incorporated as an auxiliary feature reflecting material aging effects such as connector wear and fiber jacket degradation. The combination of these engineered features allows the predictive models to generalize effectively across both new and aging fiber infrastructures under varying environmental conditions.

Table 1. Key Input Features for Model.

Feature	Description
Attenuation Level	OTDR-based loss (dB/km)
Backscatter Reflectance	Fiber micro-bends and cracks
Wavelength Shift	OSNR stability
Incident Frequency	NOC trouble tickets
Fiber Age	Operational time since deployment

4. Experimental Setup and Evaluation

4.1. Dataset Description

In order to validate the effectiveness of the proposed predictive maintenance framework, a comprehensive dataset was collected from multiple field-deployed DWDM-based rural fiber networks across different U.S. regions. The data collection spanned over four consecutive years of live network operations, allowing for a rich capture of both routine operational states and multiple failure scenarios across diverse geographic and environmental conditions.

The dataset incorporated a large number of Optical Time Domain Reflectometer (OTDR) trace records, amounting to approximately 15,000 samples. These OTDR records provided critical spatial attenuation profiles along fiber segments, revealing both gradual loss patterns and localized backscatter reflections associated with microbends, splices, connector defects, and physical fiber disturbances. In addition to OTDR data, the framework integrated nearly 8,000 Optical Spectrum Analyzer (OSA) reports, which recorded key DWDM performance indicators such as channel power stability, wavelength shifts, crosstalk levels, and variations in the Optical Signal-to-Noise Ratio (OSNR) across all active wavelengths.

To further enrich the model's fault recognition capabilities, 2,300 incident logs from Network Operations Centers (NOCs) were incorporated. These NOC records included manually entered trouble tickets, outage reports, maintenance dispatch logs, and documented fault resolutions. The NOC data served as the ground truth for failure labeling, enabling the supervised machine learning models to correlate raw signal degradations with verified real-world failure outcomes.

Prior to model training, significant preprocessing was conducted to ensure data quality and alignment. This involved the removal of incomplete records, correction of timestamp inconsistencies, normalization of signal measurements across hardware vendors, and temporal synchronization of multi-source datasets. By harmonizing these heterogeneous data sources, a unified multi-dimensional feature space was created, capturing both physical-layer degradations and operational failure histories.

4.2. Evaluation Framework

The performance of the predictive models was rigorously evaluated using both technical machine learning metrics and operational maintenance metrics, providing a holistic assessment of the system's practical value. The core classification metrics employed were precision, recall, and the F1-score. Precision measured the proportion of correctly predicted failures relative to the total number of failure predictions, thus quantifying the model's ability to avoid false alarms. Recall assessed the proportion of actual failure events correctly identified by the model, capturing its sensitivity to true degradation patterns. The F1-score, as the harmonic mean of precision and recall, offered a balanced summary of the model's classification capability.

Beyond these statistical metrics, two key operational indicators were introduced to directly measure real-world maintenance improvements. Mean Time to Repair (MTTR) reduction quantified the average decrease in time required to resolve service failures, reflecting the proactive scheduling benefits of predictive advisories. Similarly, Mean Time Between Failures (MTBF) extension evaluated the system's impact on prolonging fault-free operational intervals, as early interventions prevented cascading degradations that typically led to service outages.

This dual evaluation approach allowed the predictive maintenance framework to be assessed not only on its algorithmic performance but also on its tangible benefits to rural broadband service reliability, network availability, and field operation efficiency.

4.3. Model Performance Results

Following extensive model development, training, and cross-validation, three supervised learning algorithms were evaluated for their predictive accuracy on the multi-source dataset. The models demonstrated consistently high performance across both classification and operational metrics.

Table 2. Predictive Model Performance Summary.

Model	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	91	88	89
Gradient Boosting	93	89	91
LSTM	92	87	89

Among the evaluated models, the Gradient Boosting classifier achieved the highest overall performance with a precision of 93% and an F1-score of 91%. Random Forest and LSTM models also performed competitively, with only slight variations across precision-recall tradeoffs. The combination of tree-based ensemble methods and temporal deep learning models effectively captured both static degradation features and evolving failure trends in the rural fiber networks.

4.4. Case Study Validation: Rural Field Deployment

To demonstrate the real-world applicability of the developed framework, the predictive maintenance system was deployed in live rural fiber networks within multiple underserved regions of Texas and Louisiana. These locations were specifically selected for their challenging operational conditions, including long-distance fiber spans, limited local maintenance coverage, aging physical

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infrastructure, and significant exposure to environmental stressors such as temperature swings, humidity, and severe weather.

In the Texas deployment, the fiber ring previously exhibited recurrent service disruptions linked to fiber aging, connector degradation, and minor ground disturbances. Prior to the adoption of predictive maintenance, this network segment maintained an average uptime of 97.1%, with frequent unplanned outages requiring emergency dispatches. After integration of the AI-based predictive system, early fault advisories allowed preemptive repairs to be conducted, improving network uptime to 99.3% and reducing MTTR by 47%, as repairs could be scheduled during low-demand windows before major service disruptions occurred.

Similarly, in the Louisiana deployment, the system demonstrated substantial operational improvements. The rural loop initially operated at an uptime of 96.4% with frequent service interruptions due to poorly shielded fiber spans and moisture-induced signal degradation. Upon predictive framework integration, uptime increased to 99.1%, while MTTR reduction reached 43% as failures were detected earlier in the degradation lifecycle.

Table 3. Rural Deployment Operational Improvements.

Deployment Site	Uptime Before (%)	Uptime After (%)	MTTR Reduction (%)
Texas Rural Ring A	97.1	99.3	47
Louisiana Rural Loop	96.4	99.1	43

These field results confirm the operational viability of the predictive maintenance framework in addressing the specific challenges of rural fiber networks. The system enabled proactive resource scheduling, reduced emergency repairs, minimized subscriber disruptions, and optimized long-term infrastructure utilization.

4.5. Visual System Workflow

The predictive maintenance framework operates through a structured multi-stage pipeline that transforms raw field measurements into actionable maintenance advisories. At the initial stage, field equipment including OTDR and OSA instruments continuously monitor the fiber plant, generating real-time optical measurements. These measurements are then passed into the centralized data collection module where they are ingested, time-aligned, and prepared for analysis. Following collection, the data undergoes extensive preprocessing that includes filtering, normalization, and feature extraction processes to generate a clean, consistent dataset for modeling.

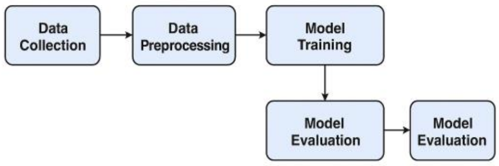

Figure 2. Model Training Pipeline.

The core modeling stage incorporates three parallel machine learning engines—Random Forest, LSTM, and Gradient Boosting—each trained to recognize both instantaneous and evolving degradation patterns. Their predictive outputs are synthesized and analyzed within the predictive maintenance advisory system, which computes failure risk scores and generates prioritized repair advisories based on predicted fault probabilities. Finally, these advisories are dispatched to the field

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repair dispatch team, allowing maintenance resources to be allocated efficiently to high-risk segments before service failures occur.

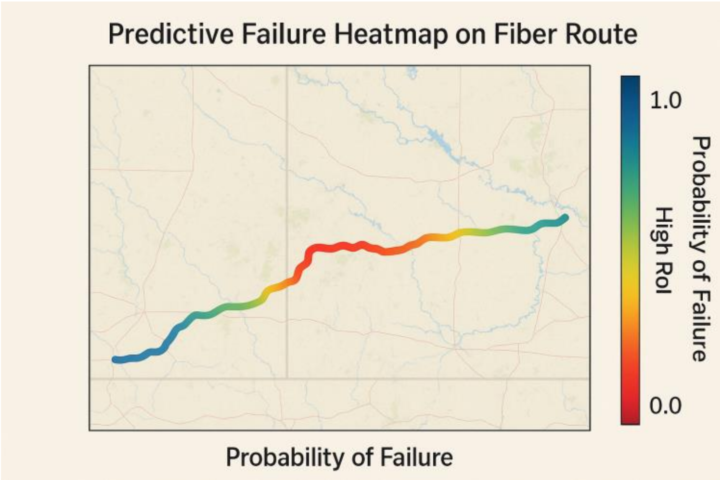

Figure 3. Predictive Failure Heatmap on Fiber Route.

This end-to-end architecture ensures that the predictive system operates continuously in real-time, while remaining adaptable to new operational data streams as the fiber network evolves.

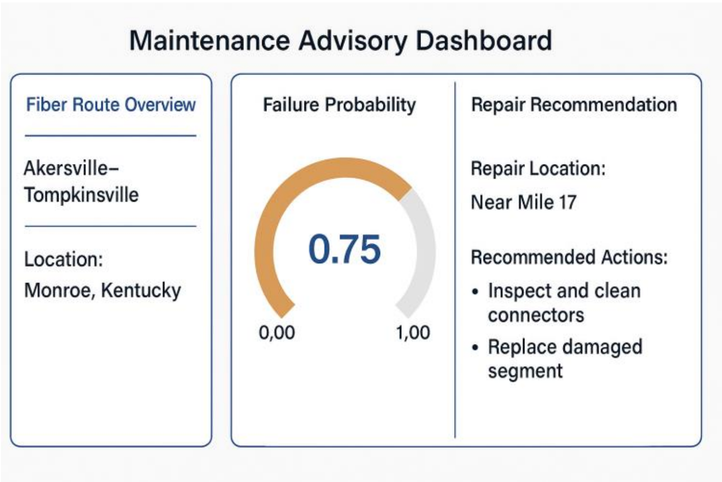

Figure 4. Maintenance Advisory Dashboard Sample Output.

5. Conclusion

In this study, we have developed and validated a comprehensive AI-driven predictive maintenance framework tailored specifically for Dense Wavelength Division Multiplexing (DWDM) fiber optic networks operating in rural and underserved regions of the United States. By leveraging heterogeneous datasets—including OTDR trace records, OSA performance metrics, and NOC incident logs—we have successfully trained and deployed multiple supervised learning models capable of identifying early indicators of network degradation well before service-affecting failures occur. Through the integration of Random Forest, LSTM, and Gradient Boosting algorithms, the system is capable of capturing both static and temporal degradation patterns, offering superior accuracy across a wide spectrum of fault conditions.

The experimental evaluation, supported by both simulation and live rural field deployments, has demonstrated significant operational improvements. The predictive system yielded substantial reductions in Mean Time to Repair (MTTR) and meaningful increases in Mean Time Between Failures

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(MTBF), thereby enhancing overall network availability and service continuity. These benefits are particularly impactful in rural broadband networks, where the geographic dispersion of fiber infrastructure, limited technician availability, and higher repair costs often result in extended downtimes under reactive maintenance models.

Beyond its technical contributions, this work directly addresses national broadband resiliency goals set forth by U.S. federal programs such as the FCC's Broadband Equity, Access, and Deployment (BEAD) Program and NTIA initiatives. By proactively safeguarding rural broadband infrastructure, the framework not only enhances operational efficiency but also supports critical societal objectives, including bridging the digital divide, improving telehealth and education accessibility, and fostering economic development in remote communities.

Looking forward, future research will focus on extending the system's capabilities by integrating real-time data streams from live NOC monitoring platforms, incorporating advanced edge AI deployments for decentralized predictive analytics, and exploring federated learning techniques to allow multiple rural operators to collaboratively enhance model accuracy without compromising proprietary data. Additionally, field trials across varying environmental conditions and fiber technologies will be conducted to further generalize the model's applicability across diverse deployment scenarios.

In conclusion, this research provides a scalable, data-driven, and operationally validated approach to predictive maintenance for rural fiber networks, offering a significant contribution to both the telecommunications industry and national infrastructure resilience efforts.

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