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Developments in Optical Fiber Network Fault Detection Methods: An Extensive Analysis

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Abstract: With the help of the continuing evolution of communication technologies, optical fiber networks have been identified to be the leading platform for today advanced data transmission systems characterized by very high bandwidth and minimal attenuation losses. However, maintaining their dependability raises a concern that forms a major problem; identifying and correcting defects likely to cause service downtime, data loss, and inefficient performances. Other conventional approaches to fault detection, such as the OTDR systems, offer basic solutions; however, their fundamental drawbacks include the issues of precision, scalability, and cost, most evident in modern large-scale networks. This paper aims at providing a detailed characterization of fault detection techniques in Optical Fiber Networks and limitation of such techniques before implementing machine learning techniques. The use of state-of-art-ML techniques such as CNNs, LSTMs, and anomaly detection models shows improved capabilities of fault prediction, fault detection, and fault classification. These approaches improve real time monitoring and control, facilitate predictive maintenance, and dispositions and resource productivity enhancing tremendously the networks availability. Through the comparison of several cases with the application of ML-based solutions for fault detection with the ordinary techniques, such as OTDR, the paper demonstrates the advantages of the proposed ML approaches to reduce the costs of network operations and to guarantee the scalability to the larger networks. These works provide the direction towards more intelligent, robust and more efficient fault ML techniques that can revolutionize the field of optical communication systems .

Keywords: Optical fiber networks, Fault detection, Machine Learning, Optical Time Domain Reflectometer (OTDR), Predictive maintenance

1. *Introduction*

The quick improvement of communication networks has moved optical fiber to the very front as the essential part, on account of their low lessening and high transmission capacity abilities. Optical fiber networks, presented in the mid-1970s, are essential for fast, dependable, and secure information transmission over significant distances, making them ideal for gigabit and past transmission [1].

However, there are decisive challenges facing optical fiber networks represented in the reliable detection of malfunctions and location, as any malfunction can lead to service interruption and data loss, in addition to possible social effects[2]. Faults can arise from different sources, such as the improper installation of cables, poor quality cables, signal inactivity, or due to external factors such as marine activities that cause damage to the under the sea or ground accidents, such as construction work or storms that cause damage to the cables Along the actual infrastructure such as roads and electricity lines [3].

To address these challenges, an effective supervision system is essential to detect and identify faults with the aim of minimizing service interruptions. Most optical networks are designed with protection systems that can quickly switch data to backup fiber paths within 50 milliseconds to ensure uninterrupted service [4].

One strategy for fault recognition in fiber optic networks is through Rayleigh scattering-based control networks, where the Optical Time Domain Reflectometer (OTDR) is a prominent procedure. OTDR allows the measurement of test pulses scattered along the fiber, providing an understanding of the integrity of the fiber without the need for controllers at each node of the network [5]. High-quality OTDRs offer superior spatial resolution (less than 20 meters) and long-range capabilities (more than 200 km), enabling efficient monitoring of entire fiber networks [6].

However; using the ODTR device has a number of drawbacks, such as its inability to locate faults precisely and notice them, particularly within the restricted range of distance measurement. In other words, its accuracy in measuring distances is limited to a specific threshold. Be-

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cause of the nature of the technology employed in OTDRs, measurements lose precision with increasing distance, and eventually the reflections become too faint to be reliably detected and processed. This implies that OTDRs might not be the best tool for testing and debugging long-haul fiber optic networks that cover hundreds or thousands of kilometers [6]..

Another disadvantage of using an OTDR tool is the high cost and complexity of the equipment. The high cost of OTDR equipment can be a major drawback for small businesses or individuals who need to perform fiber optic testing. The price of an OTDR can range from several thousand to tens of thousands of dollars, depending on the features and capabilities of the device. In addition, novice users may find it difficult to handle the intricacy of using an OTDR. To acquire reliable readings, OTDRs require proper configuration of a wide variety of settings and parameters. For individuals who are unfamiliar with fiber optic testing, it might be intimidating to interpret the findings and comprehend the numerous factors [6]..

Machine Learning (ML) is progressively used in optical correspondences and systems administration, especially in nonlinear transmission networks, optical transmission enhancement, uninvolved optical execution observing, and cross-layer network advancements for programming characterized networks [7]. ML methods have been used to address different difficulties in optical correspondences foundation, empowering exact expectation of networks execution and improving complex networks the board, fault recognition, recognizable proof of Bit Error Rate (BER), transmission of transmission (QoT), and signal enhancement [8].

Nonetheless, while critical headway has been made in using ML strategies for fault location in optical networks, especially in long stretch underground optical networks, challenges continue following hard disappointments in underground optical links [9]. Customary techniques like optical time-domain reflectometer (OTDR) estimations give the distance of the fiber link covered in the earth yet miss the mark in pinpointing the specific spot of a link cut [10].

The profundity of the channels where fiber optic cables (FOCs) are laid presents a critical obstruction in issue following, prompting postponements and income misfortune for media transmission networks. Regardless of the accuracy of OTDR in assessing fault distances, its failure to precisely find fiber cuts on the world's surface outcomes in extra expenses and asset assignment [11].

To address these difficulties, research proposes utilizing ML displaying to foresee the genuine issue area when a fiber link cut happens in underground optical foundation. By consolidating ML methods, irregularities between OTDR estimations and genuine issue distances can be alleviated, reducing delays, asset waste, and financial misfortunes for telecom networks [12].

Past exploration efforts have focused on fault following utilizing OTDR and different strategies, yet have not completely settled the issue of precisely pinpointing fault areas. Taking into account the distance of the FOC and the Euclidean distance on the world's surface, ML-based approaches mean to give more exact fault area forecasts, limiting misfortunes in the FOC networks [13].

In summary, the combination of ML strategies offers a promising answer to the difficulties associated with the following issue in underground optical networks, possibly decreasing costs and further developing the effectiveness of telecom networks [14].

The paper investigates fault discovery procedures for optical strands, starting with a conversation on issue types in view of a difficult situation ticket information from neighborhood networks in the earlier year. This investigation includes characterizing deficiencies according to type, main driver, and their effect on administrations.

Modern communication systems depend on optical fiber networks which provide fast data transmission capabilities across extensive distances. The benefits of these networks cannot prevent them from developing faults which harm operational performance and reliability levels. Substantial downtime and service disruptions result from delayed or inaccurate fault detection in these networks. Manual inspection along with basic diagnostic tools prove inadequate for detecting complex real-time problems because they perform slowly and require high costs while showing limited effectiveness. The ongoing expansion of faster and more reliable networks has created a need for improved and effective fault detection approaches capable of managing the complexities of modern optical fiber networks. The research fills the existing gap in fault detection approaches by exploring the latest innovations in optical fiber fault detection technology.

This research establishes its main purpose to investigate contemporary developments in optical fiber network fault detection approaches. Specifically, this study aims to:

1) The development of fault detection methods for optical fiber networks is reviewed with special attention to the operational restrictions of traditional methods.
2) Research the contribution of new technologies including machine learning and artificial intelligence and real-time monitoring to enhance fault detection systems.
3) Assess how modern detection systems perform in identifying specific faults through their detection of signal degradation, fiber breaks, and network congestion.
4) An examination should occur to understand the obstacles and future directions of fault detection system development that focuses on high-capacity and high-demand optical networks.

The research advances several vital aspects of optical fiber network management and fault detection sciences. This research reviews modern fault detection strategies while providing extensive details about both contemporary and traditional detection methods. The study investigates how machine learning and AI methods operate for fault prediction because this method demonstrates excellent potential for real-time automatic detection. The study demonstrates practical uses of these advancements through case examples of implemented systems which achieved success. The research identifies present shortcomings in fault detection systems while providing new research avenues to link fault detection solutions with network management systems for proactive maintenance.

2. Optical Fiber Cable

Optical fiber cable can be defined as the constitutive backbone of the fiber optic communication system, which encompasses a very thin, extended structure that strictly transports light signals produced by the transmitter with tremendous efficiency. These can be of diverse types, with either glass or plastic and are designed to transmit light signals up to certain distances with the least attenuation. There are two primary types of optical fibers used in communication systems, each with unique properties that determine their suitability for different applications: There are two primary types of optical fibers used in communication systems, each with unique properties that determine their suitability for different applications [15]:

A. Single-mode Fiber

1) Core Size: Single-mode fibers have quite a small core diameter, around 9 micrometers (micro meter) depending on the type. This results in the core being unusually narrow and the fiber only allowing for one type of light wave transmission, in other words, light within the fiber merely travels through a singular pathway in the fiber core [16].
2) Light Propagation and Signal Distortion: This makes it possible for the narrow core to contain the light in an upright column along a straight-line keeping signal distortion as resulting from multiple reflections of light at different angles (as which is the case in multi-mode fibers). This leads to better quality of signal transmission and for SMFs they can transmit signals and data over long distances more than the MMFs can [17].

B. Multi-mode Fiber

1) Core Size: Multi-mode fibers have a relatively large core diameter, which is normally in the range of 50 – 100 m. This is because the larger core diameter allows the fiber to have multiple modes of transporting the light [18].
2) Light Propagation and Signal Distortion: Multi-mode fibers allow the propagation of light rays in different ways, or modes and exist in two types close and long. Some rays go through the core at once not reflecting off the interface of the cladding and core at various angles of incidence. This feature in turn has the potential of distorting the received signal especially when the transmission path is long since it takes light beams with different numbers of reflections to get to the receiver at a given time [19].
3) Advantages and Trade-offs: Even though the signal might be affected by the reflections, multi-mode fibers can have several benefits, including easier coupling with the light source and detector chips; this makes the installation easier and possibly less costly. However, their signal vulnerable to distortion results in the smaller transmission range compared to the single-mode fibers [20].

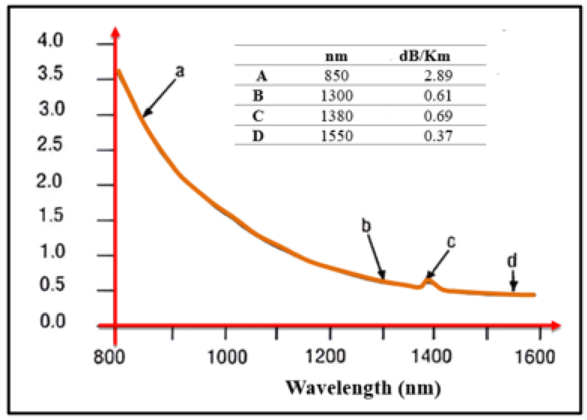

Figure 1. Attenuation Profile for Single Model Fiber

3. OPTICAL FIBER CHARACTERISTICS

A. Attenuation

Signal power in optical fiber line decreases over distance due to attenuation, it is the weakening of the light signal. Attenuation is important as it set the level of signal strength seen by the receiver so that it is able to correctly distinguish the sent signal. Therefore, it becomes essential to determine the maximum distance up which the signal can propagate given the sensitivity of the recipient and the strength of the source. Absorption, scattering and geometric losses take a part in decrease of signal next to attenuation. Expressed commonly in decibels per unit length (dB/km), attenuation is determined by the following [21].

$$a_{dB} = \frac{10\log_{10}\left(\frac{P_i}{P_o}\right)}{l}$$

Where: represents the signal attenuation, stands for the input optical power inserted to a fiber, refers to the output optical power which is received from the fiber, and stands symbolically for the length of the fiber [22]. This logarithmic unit has the advantage of solving such equations in terms of addition and subtraction or multiplication and division as well as powers and roots (Figure 1).

However, addition and subtraction require a conversion to numerical values, which may be accomplished using the following relationship: However, addition and subtraction

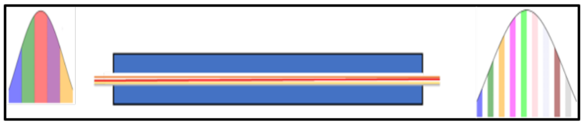

Figure 2. Chromatic Dispersion

require a conversion to numerical values, which may be accomplished using the following relationship: Where: is for the attenuation of signal, is for the input optical power that is launched into the fiber, and is for the output optical power that is received from the fiber; stands for the fiber length [23].

This logarithmic unit has the advantage of bringing into equation the multiplication and division operations and also the powers and root of the numbers by the use of addition and subtraction. However, addition and subtraction require a conversion to numerical values, which may be accomplished using the following relationship [23].

B. Chromatic Dispersion

The last thing is chromatic dispersion which is one of the greatest problems towards longer distances and accurate representation of single signals. In optic fiber communications, chromatic dispersion occurs due to the difference in the velocity with which the light signal travels through the fiber at different frequencies. There is accumulation within the optical network that leads to pulse widening and ultimately increased interference between symbols for this reason, the SNR will also reduce at the judgment circuit. As a result, in order to maintain the operational functionality of the system, more power must be provided at the receiver as is illustrated in figure (2)[24].

It is the product of two factors: MD (material dispersion) and Waveguide dispersion (WD). Since each source of light has a particular spectral band, a laser or LED source expands as it passes through the form of an optical waveguide-fiber. In the same shown waveguide, every dispersed spectral request propagates at unique band velocity. This is so because phase velocity changes with the material and the wavelength of the wave [24].

The first source is nuclear energy, while the other five are renewable energies. This is because, by the time the pulse reaches the receiver, the spectral components have separated from each other due to the different travel times and hence the pulse broadens. This is known as material dispersion Material dispersion occurs when the material through which the wave is travelling affects the relationships between the wavelengths of the outgoing waves, particularly when the frequency is being altered. Using incident wavelength 0, the dispersion coefficient for MD using the following equation (1). Using incident wavelength 0, the dispersion coefficient for MD using the following equation (2) [25].

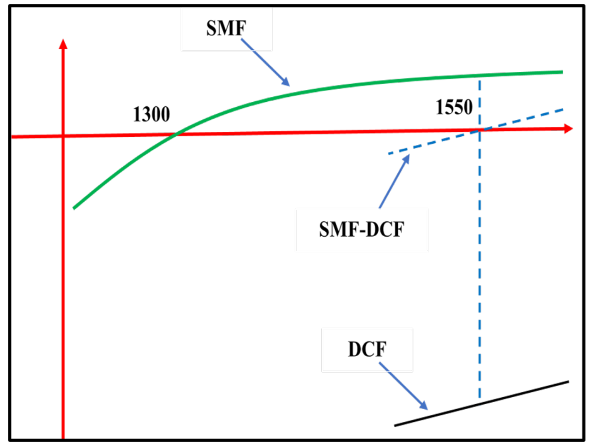

Figure 3. Dispersion compensation by DCF

C. Dispersion Compensation Fiber (DCF)

One of the major advantages of dispersion compensating fiber is that it can easily integrate with single-mode fiber networks [26]. Dispersion compensating fibers or fibers that can compensate the dispersion caused by the transmission fiber or the strand of fiber-optic cables used are known as DCFs. They derive this through a negative dispersion value which is expected to range between -300ps/nm/km. These actions act as the counteraction mechanisms and help in minimizing signal distortion with the objective of enhancing system performance. Dispersion, Kerr nonlinearity and increased SE noise are the main issues that can affect the performance of optical WDM systems. But these are problems that can be avoided if DCFs are adopted and implemented consistently. It is possible to mount it before, after or side by side to the transmission fiber and each positioning has its unique merits depending on the system requirements. Key to enhancing the design of DCF is the need to minimize insertion loss, find ways of lowest possible PMD, minimize optical nonlinearity, and have ways of improving the chromatic dispersion coefficient. Since the signal quality is a critical factor in any optical communications system, DCF (Dispersion Compensation Fiber) is important for achieving reliable systems [27]. This is due to the consideration of the Value of Discounted Cash Flow in the Dispersions equations as displayed in the Figure (3).

D. Polarization Mode Dispersion

PMD arises as a result of internal parameters and external conditions in fiber. A number of events happening through the manufacturing of fibers, the presence of flaws in the fibers, variations in the inside tensions, and so on, come under intrinsic factors leading to birefringence between the fiber and cladding. External factors are sources and influences which exert pressure and force, and change the shape, curvature, and aging of fiber optics. On account of these two factors, the two polarization modes travel with different velocities, and the transmission time to reach the receiving end is not equals [28]. Polarization mode

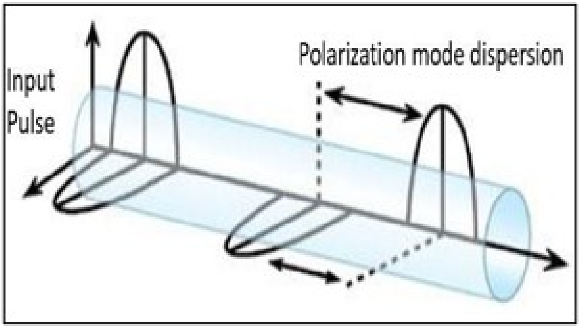

Figure 4. Polarization mode Dispersion in optical Fiber

dispersion is actually a type of dispersion which relates to the differential group delay of two polarization modes. The totally circular cross-sectional geometry is the ideal fiber geometry, which also has circular symmetric refractive index [28].

This is in stark contrast to the two quadrature polarization modes of a single-mode fiber which are two-degrees orthogonal. The differential group delay distortion between the two polarization modes during transmission is basically due to material, geometrical and stress anisotropy. This is referred to as polarization mode dispersion as shown in Figure (3-9) [28].

PMD is caused by the following factors: dam fiber, that is the geometric size of the optical fiber which is randomly manufactured in its geometry size and the residual stress in it; the refractive index distribution of an optical fiber is anisotropic; the optical cable, during its laying an in use, under external extrusion, torsion or changes in the environmental temperature or else, polarization mode coupling occurs [29].

4. FAULTS IN OPTICAL FIBERS

To detect faults in optical fiber networks, it's essential to perceive the likely sorts of deficiencies that might happen. In optical fiber networks, two fundamental sorts of faults are regularly experienced: fiber link property flaws and fiber cuts [26]. Fiber link property faults allude to issues with the qualities or properties of the fiber link itself, like imperfections in the material or assembling process. Then again, fiber cuts happen when the actual progression of the fiber is disturbed, frequently because of outside factors like unplanned harm or conscious damage. Distinguishing and tending to these flaws are fundamental for keeping up with the respectability and usefulness of optical fiber networks [27].

A. Fiber cable attribute faults

While evaluating the suitability of optical fibers for communications networks, the disadvantages of fiber cable characteristics come first. Basic transmission characteristics to consider include bandwidth, which is affected by dispersion and attenuation levels [30]. Dispersion refers to the spread of signals over time or distance, while attenuation refers to the loss of signal strength. These properties are affected by various factors, including radiation, absorption and scattering. Ensuring optimum levels of dispersion and attenuation is vital to maintaining reliable and efficient communications over fiber optic networks. [3].

B. Dispersion

In digital communications systems that use optical fibers, data is encoded in light pulses that are sent from the sender to the receiver. However, while traveling through the fiber, these pulses undergo scattering, leading to various types of signal degradation. [31]. Scattering causes the pulses to spread over time or distance, leading to phenomena such as cross-talk, where the overlapping pulses become blurred to the receiver. Dispersion in optical fibers can be classified into two main types: multiple dispersion, which occurs in multimode fibers due to differences in mode lengths and velocities, and internal dispersion, which prevails in single-mode fibers at high data rates, causing broadening of the pulses. Managing dispersion is important to maintain the integrity and performance of optical communications networks, and ensure reliable data transmission over long distances [7].

C. Fiber cable cut

The occurrence of a break in an active fiber optic cable due to work carried out at the cable site is called the "fiber break phenomenon". The extent of the outage depends on the location and number of active fiber optic cables affected by the outage. This phenomenon poses significant risks to the telecommunications industry, affecting network availability, operation, maintenance, and revenue margins [28]. Optical fiber, with its superior advantages over traditional transmission media, is increasingly replacing microwave transmission networks in telecommunication networks. However, ensuring the reliability and smooth operation of fiber optic networks, which typically transmit large amounts of data traffic, remains a major challenge [6]. Persistent fiber cuts represent a major challenge for telecom operators, as evidenced by domestic fiber optic network statistics in 2018. Faults are classified based on their impact on system parts and services and root causes. In backbone networks, where fiber cable lengths are much longer than in metropolitan networks and the number of nodes is higher, protecting the cable length is vital due to the higher failure rate.[32].

5. FAULT DETECTION IN UNDERGROUND OPTICAL NETWORKS

Failures in optical networks mainly appear in the form of losses, which significantly affect the quality of transmission (NoT) and overall quality of service. These faults are usually classified into two main categories: hard faults and soft faults. Hard faults are sudden events such as fiber cuts or outages, while soft faults involve gradual degradation, often due to equipment failure or channel misalignment [33]. Multiple sources contribute to failures in optical networks, including channel misalignment, booster failure, and fiber kinking. Soft faults, in particular, can lead to signal degradation and bit error rate (BER) variations at the receiver, which can lead to packet losses or service interruptions [34].

While soft malfunctions are usually treated using specialized detection techniques, difficult faults in the underground networks, such as cutting and sprains in fiber cables, are usually followed and usually determined by using OTDR. However, the use of OTDR is accompanied by a set of problems as we mentioned earlier, causing difficulties for the cable repair teams to determine the exact location of the malfunctions in the optical fiber cable. This situation prolongs the period of disruption of the service, increases revenue losses and losing communication services for users [6].

A. OTDR

An Optical Domain Time Reflector (OTDR) is a pivotal device for tracking faults in optical cables. Its working principle is based on the use of Rayleigh scattering and Fresnel reflection techniques to accurately measure fault distances. In addition, OTDR is used to check for loss of links, measure cable length, and identify faults in optical cables, especially during initial installation [7][35].

When an OTDR sends a high-power optical pulse through a fiber, Rayleigh scattering occurs, producing a feedback signal that reflects faults in the cable and returns to the device. This returned light is detected by a sensitive photoreceptor, converted into digital form, and the signal is averaged to improve the signal-to-noise ratio. The resulting data is displayed as a graph, providing a visual representation of backscatter activity, including cuts, link losses, bends, attenuation, and fault distances in the optical network [36].

Fresnel reflection, another technique used by OTDR, detects discrete reflections caused by changes in refractive index elements, such as air gaps or particles that obstruct the flow of light. These reflections show fault locations, and by analyzing Fresnel reflection data, OTDR can predict both soft and hard faults in grid infrastructure[37].

In addition to Rayleigh scattering and Fresnel reflection, OTDR can use other analytical principles such as Raman scattering, Mie scattering, and Brillouin scattering to trace faults in optical networks. These principles allow OTDR to accurately measure underground fiber cable distances, enhancing fault detection capabilities under various conditions [38].

B. Tracing Optical Network Faults

Fiber optic network troubleshooting is a critical activity as it helps identify flaws with the aim of enhancing the stability of these networks. It is often initiated by detected signs that include poor performance, signal attenuation, and so on. There are different methods of identifying faults, such as OTDR – which involves the transmission of light pulses along the fiber and whose reflections indicates the presence of faults; and VFL which uses visible lasers to indicate faults and breaks or bends in the fiber. Optical Power Meters and Optical Spectrum Analyzers (OSA) are instruments that respectively measure the signal power deviation and variations of the signal spectrum. Other fault isolation techniques such as the sectional and loopback testing aid in making a narrowing down of the fault[39]. NMS continuously monitor alarms and performance to distinguish early signs of problems hence are important in the network. Once a fault is realized, then instruments such as the OTDR can be used to measure distance to the slash and mapping of the topology assists in figuring out the exact physical placement of the slash. Analyzing repair and maintenance, some of them consist of splicing of damaged or cut fibers, cleaning or replacement of connectors, and replacement of any bad networking part. The post-repair tests guarantee that faults found have been corrected while monitoring as continued helps in keeping a check on the efficient network [40].

C. Faults in the current Fault Tracing Techniques

Despite the advancement of current technologies applied in fault tracing techniques for optical networks, one can identify certain weaknesses. OTDR and OSAs are expensive tools which are not easily affordable by many firms especially those that operate in narrow fields; they require keen training to be used on the field. Also, while OTDR is good at fault identification, it may not be as accurate when it comes to determining the exact location of the fault, particularly when the network is highly branch or geographically entangled; also may provide insufficient data resolution in case of short fiber segments. Another weakness of some fault tracing tools is that they are selective in the types of faults that they can detect; for example, while OTDR works best when the breakage or severe bending of the fiber is present, it may not be able to recognize minor signs such as the wear and tear of the connectors as well as alignment problems with the fibers. Some forms of tests like loop back test may be invasive and can cause interruption in the network services and this is un desirable in heavily reliant applications or systems that run 24/7 [10].

There is also often manual intervention required in fault tracing processes, and this may take a long time in writing and can also involve human error. Due to the character of the sensor data, numerous external disturbances like temperature variations and mechanical vibrations may influence the precise detection of the fault. The major challenge with legacy fault tracing methods is that the existing techniques may become resource-intensive and time-consuming with increasing network size and complexity of optical networks, thus resulting in extended detection and repair times [41]. Secondly, the integration of fault tracing tools with the existing network management platforms can be cumbersome and whose integration offers operational complications with the systems. Thus, the further development and improvement of fault tracing techniques pinpointed their current weaknesses and the need for their elaboration to suit today's characteristics of optical networks [11].

D. Advancing Optical Network Fault Detection with Machine Learning Techniques

Machine learning can greatly enhance the deficiencies of the conventional OTDR by applying superior predictive algorithms fit to handle complex and high-dimensioned data patterns. A critical weakness of Traditional OTDR methods is the ability to determine the exact position of the fault, more so in large or complex networks. Machine Learning algorithms like SVM, CNN, LSTMs and others offer a high level of accuracy in identifying anomalous behavior in the network by training the model with historical data along with real time inputs. These algorithms not only detect faults with higher accuracy but also categories the kinds of faults into fiber cuts, bends or signal degradations, overall enhancing the diagnosis of a fault [42].

Due to its ability to update from current signals gathered from the network sensors in real-time, the use of ML-based systems greatly minimizes false positive and negative results, which are prevalent in other conventional approaches. Predictive maintenance, which is one of the most important use cases of ML, strengthens network stability even more by predicting possible failures in accordance with past incidents and environmental conditions[43]. This preventive strategy enables the operators to solve problems before they degenerate to major problems that have a negative impact on the system's availability, repair costs, and continuity. These capabilities enable ML as a revolutionary framework in the current optical network fault management [44].

6. APPLICATION OF MACHINE LEARNING IN OPTICAL-NETWORK FAILURES

Machine learning (ML) is progressively being applied to address difficulties connected with optical network disappointments. Here are a few key applications:

Fault Location and Classification: ML calculations can investigate information gathered from optical networks, including OTDR follows, to recognize and arrange various sorts of deficiencies, for example, fiber cuts, twists, and sign corruption. Via preparing models on verifiable information, ML can distinguish designs demonstrative of explicit kinds of disappointments, empowering proactive support and quicker issue goal [45]. Predictive Maintenance: ML models can foresee expected disappointments in optical networks by breaking down different boundaries like sign strength, lessening, and natural circumstances. By checking these elements continuously and contrasting them and authentic information, ML calculations can gauge when and where disappointments are probably going to happen, permitting administrators to make preventive moves before issues heighten [27]. Anomaly Detection: ML procedures, for example, unaided learning can recognize oddities in optical network conduct that might demonstrate looming disappointments or strange circumstances. By ceaselessly checking network execution measurements, ML calculations can recognize deviations from typical activity and trigger cautions for additional examination [34]. Optical Signal Quality Optimization: ML calculations can upgrade optical sign quality by changing boundaries, for example, power levels, regulation arrangements, and scattering pay settings because of changing network conditions. By gaining from past execution information, ML models can powerfully adjust network setups to amplify signal quality and limit the gamble of disappointments [32]. Dynamic Steering and Asset Allocation: ML-based traffic designing calculations can upgrade directing choices and asset allotment in optical networks to moderate the effect of disappointments and guarantee productive utilization of network assets. By dissecting traffic examples and network geography, ML models can powerfully reroute traffic around bombed connections or hubs to keep up with administration progression and limit clog [46]. Performance Forecast and Limit Planning: ML models can anticipate future network execution and limit prerequisites in light of verifiable information and projected development patterns. By estimating traffic interest, transmission capacity usage, and asset accessibility, ML calculations can assist administrators with arranging network overhauls and extensions to forestall bottlenecks and oblige expanding request [47][48].

In general, the utilization of ML in optical-network disappointments holds extraordinary potential to improve network dependability, effectiveness, and execution by empowering proactive fault discovery, prescient upkeep, and canny asset the executives.

7. Advantages of ML techniques in Fault Detection and Classification in Optical Networks

- Detecting and classifying errors in fiber optic networks using artificial intelligence techniques achieves many unique advantages, including:

- High accuracy: AI algorithms have the ability to detect and classify errors with high accuracy, reducing false positives and negatives.

- Real-time monitoring: AI-based systems can continuously monitor fiber optic networks in real-time, allowing immediate detection and response to faults.

- Scalability: AI algorithms can scale to analyze large amounts of data from complex fiber-optic networks, making them suitable for deployment in diverse environments.

- ·Adaptive learning: AI systems can adapt and learn from new data and experiences, improving error detection and classification capabilities over time. As Bill Gates once observed, "The progress of technology depends on making it so convenient that you don't really notice it, so part of everyday life." AI-based fault detection and classification is seamlessly integrated into existing network management workflows, enhancing overall operational efficiency [2].

8. RELATED WORKS ANALYSIS

Fault detection and order assume a critical part in guaranteeing the unwavering quality and proficiency of different networks across various spaces. Table 1 gives a thorough outline of ongoing exploration endeavors pointed toward addressing different difficulties connected with issue identification and order. The examinations cover many applications, including optical networks, sensor networks, modern cycles, and Web of Things (IoT) conditions.

Ali [3] examines some of the most familiar problems that occur in optical fibers including fiber breaks, high attenuation, and dispersion. The research thus employs a critical analysis of published papers, white papers, and articles to present a broad analysis of existing fault detection techniques. Including important problems and ways to solve them, this paper provides important information useful for the researchers and practitioners in the field of optical communications. However, due to the fact that the research analysis relies solely on the literature review, there may be incomplete representation of new fault detection techniques or new technology that may not have been explored in detail in literature.

Khan et al. [7]: provide a comprehensive, technical review of the use of ML techniques in optical communications and networking. The study revisits ML concepts by relating communication theory and signal processing to mathematical concepts. The authors describe how these methods can help to improve and perfect various aspects of optical networks. Though the study provides a good theoretical background of the principles of ML and the contribution of these ideas to optical communications, the practical problems of implementing such solutions or further advancements in the general field of network ML techniques are not discussed, which should be looked at in future research.

Abdelli et al. [11]: presents a new method that involves a hybrid of the denoising convolutional autoencoder (DCAE) and bidirectional long short-term memory (BiLSTM). In particular, the DCAE effectively denoise the OTDR signals, the BiLSTM reaches 96.7% of fault detection rate, and is considerably better than the models trained on noisy signal by 13.74%. The proposed non-iterative approach is shown to have a very low level of noise and enhances the diagnostic accuracy as well; however, its efficiency has to be tested in a wide range of real-world scenarios with different noise settings.

Patri et al. [49]: concern themselves with the application of ML algorithms in the diagnosis and identification of failures in OSaaS networks. Based on flexible bandwidth variable transceivers telemetry data, this paper compares and assesses dynamic artificial neural network model with threshold and one-class support vector machine. The results are explainable with checks that demonstrate the efficient failure detection and identification in OSaaS networks. However, the research only considers particular network configurations and test time, it implies the potential of future studies in more generic and complex networks.

Liu et al. [50]: AI-assisted fault location methodology for higher density interconnectivity system in data centers is proposed. By adding a customized AI module to an optical power monitoring system that can be incorporated into an OTDR device, the approach delivers a shocking 98.41% efficiency of failure detection. The AI module is used to provide an ability to predict the most likely optical link failures which helps to increase the network's availability and reduce the time required for its maintenance. The effectiveness is shown specifically in data center using spatially varying PDs, although further work is necessary to extend this method to other less structured or general optical networks.

Goni et al. [51]: the author presents a fault detection and classification technique for transmission line (TL) to enhance stability and power supply reliability. In the design of the system, data simulation is done by using MATLAB Simulink while fault classification is done by using the Extreme Learning Machine (ELM) algorithm. The approach obtains high classification accuracy for both faults and their types, and at the same time, decreases computational cost compared to the neural network approach. But due to the nature of the top layer which focuses on simulations, the system will require credibility tests and real-world TL operations to assess the feasibility and reliability of the system.

Villa et al. [52]: identifies 96 papers from the overall database of 841 papers for a systematic mapping analysis to study the use of machine learning in optical networks. The paper demonstrates that supervised ML approaches are applied mostly to resource control, anomaly detection, network observation, and traffic identification. Moreover, it highlights the future research direction in terms of the application of ML for optical networks. Nevertheless, the majority of the analyzed studies were performed in a laboratory settings, indicating the importance of further real-world research to achieve these approaches' full potential.

Kruse et al. [53]: describe a new soft-failure management paradigm for optical networks that uses a GAN with VAE structure. Limited training data is one of the areas that make this machine learning-based approach stand out in detecting soft failures. Comparing the results with other methods, the superiority of the developed VAE-GAN framework is proved. However, the proposed study is applicable only in the experimental environment, though its extension to real optical networks with dynamic conditions is still an open question.

Lindström et al. [54]: focuses on the application of the supervised machine learning algorithms for pulp testing in the pulp and paper industry including Lasso regression, support vector machines (SVM), feed-forward neural networks (FFNN), and recurrent neural networks (RNN). Based on fiber suspension micrograph data, it discovers that the accuracy of the proposed FFNN model is up to 81% with Yeo–Johnson preprocessing technique. The study shows that ML offers a fast, accurate and relatively inexpensive pulp testing in contrast with conventional methods. Nevertheless, its applicability is restricted through the particular applied techniques and software, which require further tuning for more general manufacturing environment.

Singh et al. [55]: introduce a bio-inspired machine learning approach for the detection of DDoS attacks in fiber-optic networks, the Sea Lion fine-tuned Long Short-Term Memory (SL-FLSTM) model. The developed approach reveals high performance figures, such as the recall of 98.1%, the precision of 98.2% and accuracy of 98.4%, higher than in the best-known models. The SL-FLSTM incorporates knowledge about sea lions to distill and enrich sequential data analysis and embrace long dependency learning. Compared with DDoS attack prediction, it has not been tried for other kinds of cyberattacks or other situations.

Manzoni et al. [56]: concerned with fault detection in continuous glucose monitoring sensors in artificial pancreas systems. In the present research, faults are realized if there are differences between the actual and the predicted values with the help of a Kalman predictor. This model-based approach enables the consideration of system dynamics and provides a more accurate fault detection technique. But compared with other algorithms, it needs an accurate system model and prediction, which may restrict its expansibility in various clinical applications.

Jihani et al. [57]: presented A parity space approach detection and isolation of Wireless Sensor Networks (WSNs). This method relies on use of mathematical models to detect faults from large differences between the measured and computed values. This strategy applies the redundancy characteristic of measurements obtained from sensors to identify discrepancies. Although the method is useful for fault detection, it has a disadvantage of model construction that is necessary for accuracy which may not be suitable for unknown WSN environments that are dynamic or unpredictable.

Hashimoto et al. [58]: describes a multimodal fault detection of internal sensors in mobile robots using Kalman filters. The method calculates mode probabilities from the sensor gain applicable for fault decision at multi-failure mode. This robust approach is suitable for complex robotics systems because it can cope well with various failure situations. Nevertheless, it depends upon the precise estimates of the Kalman filters which may be difficult to attain specifically in noisy settings or when there are discrepancies in the models.

He et al. [59]: proposes a fault identification model for identifying faults in optical fiber sensors in aero-engine systems taking into consideration disturbances and uncertainties. The approach was assessed using a model of a gas turbine, where the ability of the technique in detecting sensor faults was also established. The method shows the performance reliability when system uncertainties are included in the model. But it may not be very effective in the situations where it is hard to model the system accurately because of its high dependence on the modeling of system dynamics.

Yan et al. [60]: apply a KPCA-DL-BiLSTM model to identify minór soft faults of air conditioning sensors. The utilization of KPCA in combination with deep learning and bidirectional LSTMs has better fault detection capability than each method alone. It is the most sophisticated approach to the diagnostic and allows enhancing sensor reliability due to the detection of even the slightest imperfections. However, in the present work, its performance is relatively good in detecting faults for a specific system, but it could be less optimal for other types and complexities of faults and hence needs further development.

Alwan et al. [61]: use time series clustering approach to identify long segmental faults in sensor nodes. This method allows for a more effective means of detecting long-segmental outliers than predictive analysis. When it clusters time-series data, it identifies patterns that are out-of-the-ordinary, pointing to faults. The idea of the method is quite sound and has fairly good performance, however, it completely relies on the input data quality and representativeness, which can be an issue in various or noisy conditions.

Zhao et al. [62]: focuses on the identification of an elementary method that uses a sliding window and control limits in determining early indications of faults in industrial processes. By analyzing deviations such as constant bias and precisions within a window, the method is successful in identifying early-stage faults. The approach is relatively uncomplicated and one based on empirical control limits, it is therefore readily applicable. Though, the use of FMI method is restricted to certain types of faults and industries or processes, and thus is not very versatile.

Uppal et al. [63] : examine the early fault prediction in Internet of Things systems using machine learning algorithms. The study shows that ML helps improve fault prediction by achieving a classification accuracy of 94.25%. The approach also shows a proactive technique for keeping the system reliable by reviewing IoT-generated data. Yet, its effectivenessdepends on the datasets and algorithms chosen, which should be optimized depending on the IoT application area.

Wahid et al. [64]: introduces a CNN-LSTM framework for the prognostic analysis of machine failures through time series. CNN works for the feature extraction part while LSTM is used for processing the sequential data. The model is also quite credible and therefore provides forecast results efficiently for optimal maintenance and minimum time out of service. However, its performance depends on the quality and quantity of the training data, and thus may not be flexible to different industrial environments.

Uppal et al. [65]: use machine learning algorithms to classify faults in IoT connected office appliances. Thus, the study contributes to the development of a reliable system for the analysis of IoT data, for further classification of faults and optimization of the performance of connected devices. Thus, the performance of the suggested approach can be rather high but strongly depends on the amount of complexity in the appliances and the number of potential fault cases, thus requiring additional investigations for diverse applications.

Safavi et al. [64]: consider the feature extraction and a multi-class Deep Neural Network (DNN) to predict the health status of electronic sensors in self-driving cars. The paper recognizes a number of faulty sensors and explains how fault types can be categorized, and how new and improved levels of sensor reliability can be realized using state-of-the-art ML methods. But the method's success depends on reasonable extraction of features and complete labeling of faults, which may be a problem in real-world applications with a wide range of sensors.

Wong and Haron centered on the design of an intelligent fault detection framework for fiber optic cable infrastructure. For fault detection, the received light source was monitored by ESP 32 and an IR Brightness Sensor. Connection to the Blynk application enabled monitoring and controlling of cable faults in real time. The methodology focused on the fact that with accurate localization of potential faults, the repair time and manpower could be minimized without needing to excavate a large area. The findings revealed that this strategy improved telecommunications operations greatly and reduced total expenses as well, guaranteeing service dependability by identifying and repairing broadband issues more effectively [66].

Soothar et al. used higher order ML and DL technologies to diagnose and identify errors in optical fiber systems. In this work, OTDR_Data was used as a dataset and other classifiers like SVM, RF, and a CNN-LSTM model were employed. Other techniques that were adopted under Ensemble Learning were also used to boost the accuracy. The study successfully attained 99% accuracy but at the same time took additional time of 360 seconds using the CNN-LSTM model. The proposed Ensemble Learning was used to improve fault detection accuracy on multiple classifiers, indicating that the proposed technique could be used to increase fiber optic system reliability through effective identification of faults [45].

Qu et al. analyzed how Li-ion batteries contained advanced optical fiber sensors to detect subtle physical and chemical transformations. There was also an opportunity to perform real time in-situ measurements of various parameters, including stress, strain, temperature, and the concentration of ions using Fiber Bragg Grating (FBG) sensors. Such sensors provided information about the state of batteries, electrolyte, and safety conditions of batteries. The author of the study suggested that these innovations can improve battery efficiency, reliability, and safety by giving a comprehensive view of their operation and open avenues to advancing smart battery systems that will make batteries long-lasting and efficient [44].

Hazim and Mahmood provide an extensive evaluation of traditional as well as modern fault detection procedures in optical fiber networks. The paper demonstrates OTDR's restricted ability to detect faults in extensive distances through networks while introducing machine learning methods which incorporate CNNs and LSTMs to boost detection precision. The study evaluates both standard and AI-based predictive maintenance approaches by showing how implementing AI leads to lower operational expenses and shorter network outage periods [67].

Abdelli et al. developed a fault detection system that merges DCAE with BiLSTM network to handle fault identification and categorization in optical fiber networks. The proposed model demonstrates better performance than standard OTDR systems by detecting faults with a 96.7 perecent accuracy level. The research finds AI technology essential for predictive diagnostic work and fault localization because it decreases maintenance durations while improving network service dependability [68].

Liu et al. developed an AI-enhanced failure identification system for dense optical networks which combines customized AI operations with optical power surveillance hardware. The method provides 98.41 percent accuracy for fault detection which shortens the time necessary to determine problems within extensive networks. Real-time fault detection benefits from AI-powered analytics when integrated into network management systems according to this study [69].

A detailed analysis of machine learning application in optical networks appears in Khan et al. (2024) through their examination of predictive maintenance together with real-time anomaly detection and self-healing network capabilities. The research finds growing industry implementation of artificial intelligence models including Support Vector Machines (SVMs) and Random Forests (RF) for network fault detection and prediction purposes. The article outlines the difficulties of ML implementation involving big training data requirements and immediate data processing needs [70].

The research by Kruse et al. demonstrates how Generative Adversarial Networks can successfully address soft failure management in optical fiber networks. AE-GAN models used by their study reveal the capability of identifying fiber optic cable degradation during its early stages which enhances preventive maintenance operations. The suggested method overcomes traditional fault detection systems by producing fewer false alarms while simultaneously improving prognostic functions. The research points towards the need for additional analysis of deployment hurdles which include both computational performance issues and integration difficulties [71].

A new method of fault detection through optical fiber sensing utilizes Raman scattering combined with Fiber Bragg Grating (FBG) sensors according to Qu et al. (2024). The implemented methodology allows continuous network observation which detects minute physical along with chemical alterations occurring within optical fibers. The research demonstrates that optical fiber sensors become viable components for smart grid and industrial monitoring systems which improve fault prediction accuracy while decreasing network failures [44].

Tangudu and Sahu (2024) discuss OTDR-based detection boundaries by introducing an AI-driven predictive analytics system linked to OTDR devices. The industry utilizes OTDR as its primary fiber fault detection tool but this method shows limitations when trying to precisely locate faults over extended distances. The authors implement deep learning techniques which boost fault detection precision in subsea and buried fiber networks according to their study results [72].

These points can summarize the above works:

- OF fault detection or identification is another important frontier in solving reliability and continuity of services challenges in networks.
- Fault detection and identification, resource management, or system reliability are the main applications of machine learning (ML) and deep learning (DL) in the optical networks.
- Optical fiber technologies are being used not only for networking, for example, for blood monitoring and battery diagnosis, the emphasis is made on real-time and high-sensitivity uses.
- Increase the use of real-life situations as a way of testing the effectiveness of the technique in order to check the applicability of the methods in ever changing environments.
- Enhance the models themselves so that they are able to incorporate noisy and inconsistent data easily.
- More experimentation of the methods such as CNN-LSTM and DCAE-BiLSTM in other electrical networks and industries.
- Discover more interdisciplinary use cases that use optical fiber as the core infrastructure along with IoT, edge computing, and quantum sensing.

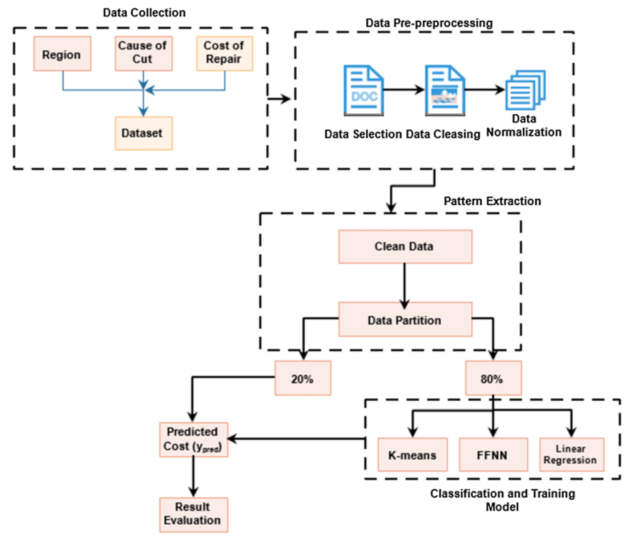

Figure 5. methodology Idea

- Instead, efforts should be directed to lowering the cost of such technologies to enhance its use among clients.

9. New Methodology Idea

The proposed methodology depicted in Figure 5 uses diverse regression models of machine learning and deep learning to perform accurate fault distance predictions within fiber optic networks. The regression tools serve as fundamental analytical tools that measure how input variables affect the continuous output parameter of fault distance. Traditional machine learning algorithms including Random Forest (RF), XGBoost, AdaBoost and K-Nearest Neighbors (KNN) and Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT) and Linear Discriminant Analysis (LDA) were used because of their ability to process diverse data formats with improved performance and reduced errors. Convolutional Neural Networks and Recurrent Neural Networks together with Long Short-Term Memory served as deep learning models to extract nonlinear patterns from time-series data. The combination of time-series analysis through LSTM-RF and CNN-RF with boosting benefits regression accuracy.

The approach includes performing data preprocessing on raw data to remove gaps and clean it while encoding the data before splitting the dataset to establish training and testing segments for proper model evaluation. The evaluation process relies on three statistical measures including Mean Square Error (MSE) and Root Mean Square Error (RMSE) and R-squared (R^2). The most effective model becomes the saved model for generating precise and reliable predictions on fresh datasets. Results are displayed through visual data presentation tools which allow effective examination of prediction results and reveal important findings. The proposed method provides both practical and efficient capabilities to detect optical network faults alongside their location information which benefits optical network management operations.

A. Methodology Discussion

The outcome of this research confirms that the combination of different machine learning and deep learning models creates superior accuracy and reliability for predicting fiber optic network faults. RF and XGBoost traditional machine learning algorithms together with deep learning models LSTMs and CNNs show their power to detect the complex non-linear patterns found in optical network data. The results show that machine learning techniques hold great potential for improving fault detection and localization in networks which allows better real-time decision-making and maintenance practices. Hybrid approach models consisting of LSTM-RF and CNN-RF showed better performance levels which proves that fusion of time-series analysis with regression boosting techniques brings valuable advantages to predictive tasks. Research indicates that network managers would benefit from implementing multi-model approaches because it produces better network reliability which leads to enhanced optical fiber network performance.

Artificial intelligence along with machine learning has become fundamental in telecommunications through its development of predictive fault detection capabilities according to this investigation. The rise in internet service speed expectations requires precise fault distance estimation as an essential factor to sustain product quality and decrease service interruptions. The proposed method in this study delivers an implementation-friendly approach for network providers which allows them to solve problems ahead of time while maintaining best network performance. Machine learning in conjunction with deep learning enhances error prediction accuracy while setting the path for automatic repair solutions. Networks operated by automated systems that use models from this study have the ability to detect and identify faults while automatically resolving issues without human involvement. Self-healing networks obtain great value from automated systems because they work efficiently with complex and large-scale network environments which require costly human intervention.

The research presents encouraging results although future work must overcome various restricting factors. The study relies on a limited set of data that originates mostly from the IEEE Data port database. This dataset delivers important information about optical networks, yet its ability to predict different network types beyond IEEE Data port limitations emerges. Additional research is needed to analyze larger diverse datasets so that scientists can confirm how well the models perform across different network configurations. The study failed to address real-time deployment challenges of these predictive models in operational network management systems even though they showed effective accuracy rates. The implementation of deep learning models by smaller network operators that have limited resources faces challenges due to their high demand for computational assets. Future research should develop methods which optimize these network models for implementation while maintaining their operational performance criteria. The research examined fault distance prediction through supervised learning techniques as its main subject. Researchers should conduct studies of unsupervised and semisupervised learning methods in upcoming work, particularly for cases where available data are scarce or hard to label. Such approaches enable model development for identifying unrecognized faults or anomalies that function without relying on large labeled dataset resources.

Future research needs to develop multiple promising approaches to build upon this current work. First, cross-network validation is needed. Research based on different datasets from various optical networks across different regions and environmental conditions and cable types and network structures would help determine the models' general validity. Implementing the developed models in real-time operations should be emphasized as a second priority. The models should be integrated within network systems to monitor faults which will allow automatic fault identification and corresponding real-time remediation through predictive actions. The implementation of hybrid fault detection systems that integrate machine learning methods with emerging technologies like IoT-based sensing and 5G networks would create more complete system capabilities for fault detection. Future research needs to concentrate on model optimization together with resource usage optimization. Integrating model compression techniques and edge computing research will create computational methods which match production needs of limited power networks. Research must focus on understanding model interpretability in its final stage. Deep learning models will become more understandable to users for critical applications through the application of interpretability methods such as LIME or SHAP.

10. Conclusions and Future Work

The current work has extensively analyzed the innovations and issues of flaw detection and identification in OFN and pointed to the key role of the ML and DL. Optical fiber cables which boast unlimited bandwidth and almost zero attenuation losses are the central part of the existing telecommunication systems. But the progressive reliability and efficiency of their systems call for advanced methods of fault detection to reduce service outages and data loss while enhancing overall performance. Conventional fault detection techniques like Optical Time Domain Reflectometers (OTDR) have always served well in optical networks, but they lack the precision, scalability and, affordability. These deficits are especially apparent in large-scale complex networks and therefore require the creation of new attractive solutions that would suit the needs of the contemporary networks.

The integration of ML and DL into fault detection procedures has shown enhanced predictability, fault categorization, and monitoring functions. Hence, CNNs, LSTM together with the novel DCAE-BiLSTM have been proven to be efficient methods for improving the reliability of the network. These approaches do not only enhance the accuracy of fault detection but also contribute to the realization of predictive maintenance, decrease of operational costs and increase of scalability, which are applicable for large-scale systems.

Apart from networking, other optical fiber technologies are finding application in other areas including, blood monitoring and battery diagnostics. These applications are based on two major characteristics of the optical fibers – real time and high sensitivity and demonstrate their versatility to various and multi-disciplinary fields. Further studies should focus on enhancing the optical fibers' application in other exciting fields, including IoTs, edge nodes, and quantum sensing.

Future development should concentrate on increasing the use of real-world dependability testing to prove the functionality of fault detection methods under real conditions. It is also necessary to improve the robustness of ML models to deal with noisy and inconsistent data to achieve dependability across numerous applications. In addition, expanding research into other uses of ML-based techniques, including CNN-LSTM and DCAE-BiLSTM, in other industries and network environments further holds the potential for even higher growth. Last but not the least; the high cost of these optical fiber technologies will have to come down since their uptake will be critical to the success of networks that rely on this technology.

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