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Fault Identification in Optical Transport Network Using CNN

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Abstract: - The growing diversity Regarding the provision of information and services transmitted Using optical technology transport networks (OTN) has made network survival a crucial issue in current study. Fault detection refers to the process of identifying faults that arise from various issues such as packet loss, disconnection, and others in the OTN. The determination of the fault location in an OTN is highly significant in the analysis of the resilience of optical networks. This study presents a fault diagnosis system that utilises a Convolutional Neural Network (CNN), focusing primarily on distinguishing between hard faults (HF) and soft faults (SF). The CNN is implemented in where the fault is situated domain of OTN to determine the presence or absence of potential fault locations. The notion An F-Measure is implemented in order to quantify the impact of positioning.utilising Location, time, mean squared error (MSE), and F-measure. The scientific investigation demonstrates that the suggested CNN neural network achieves the highest performance. The suggested CNN has a reduced localization time and achieves an F1-score of 0.98 after 85 iterations. This level of accuracy and real-time performance fulfils the requirements for fault identification. Hence, there is significant potential and practical utility in incorporating neural networks in the field of identifying and locating faults in optical transport networks.

Keywords: Optical transport networks; failure localization; artificial neural network; CNN, F1-Score, MSE.

1. Introduction:

With the development of optical network technology, the number and type of information and services it carries are constantly increasing, and the access mode and the network mode of services are also improving. The OTN is increasingly responsible for transmitting a greater volume of data as the primary infrastructure for future generations. Simultaneously, OTN utilises several service signals, such as SDH and Ethernet IP, to achieve efficient, rapid, dependable, and transparent transmission. Currently, the network rate interface of OTN may achieve a maximum capacity of 400G. In a sophisticated and advanced optical transport network that operates at ultra-high speeds and has a large capacity, any network malfunction will lead to a decrease in how good the service is (QoS) of the network. This might potentially result in the loss of a significant quantity of information. Therefore, the resilience of optical networks has become an important topic in optical research, and the accurate identification of OTN faults is crucial for studying the survival of optical networks.

Recently, due to the increasing need for extensive data processing and thorough analysis in numerous sectors, data mining has emerged as a prominent and challenging area of computer science. Data mining is an interdisciplinary study subject within computer science. The research techniques in this field have strong connections with other areas, including math, statistics, expert systems, social networks, natural language processing, machine learning, and Figuring out patterns [1]. Despite the significant advancements in the field of data processing and data mining across various disciplines,

the utilisation of OTN remains limited compared to other disciplines, and its use is not yet fully developed. In the future, the OTN network, which serves as a A high-capacity backbone transport network will be established. require intelligent scheduling and aim to minimise manual operation.Currently, OTN often employs its own autonomous network element management system to handle network management.[2][3].The warning information is displayed in a distinct manner, resulting in a complex network issue diagnostic process that typically requires user intervention. Proficient network administrators are needed to promptly analyse and address fault characteristics and correlations[4]. This study primarily utilises The fuzzy set theory and neural networks for analysis, employing Indicators like F1-Measure for evaluation. The following are things that artificial neural networks (ANN) do:attributes: not being linear, high resilience and acceptance to faults, Similar to distributed doing things techniques, self-learning and adaptive capabilities, and rapid processing of both quantitative and knowledge of the quality[5]. Hence, the application of fake neural networksnetworks in where the fault is domain of OTN might be considered. The article utilises two types of neural network models: BPN stands for "back propagation network" and RNN for "recurrent neural network.").

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The notion of the BP (back propagation) neural network was introduced by scientists Rumelhart and McClelland in 1986 [6]. The neural network as many layers as possible and is taught using the error reverse propagation method. At the moment, it's the neural network that is most extensively employed. The primary objective of a RNN is to handle and forecast sequential data [7]. Both BPN and RNN are employed for the purpose of analysing the alarm signal and identifying the problem spot in the OTN, hence facilitating the precise localization of the defect. The concept of fuzzy set theory is presented in the field of fuzzy mathematics, where the probability value for fault location is determined within the range of 0 to 1. The chance of each potential fault site is determined by the magnitude of its corresponding probability. Nevertheless, these two models also possess their individual shortcomings: The BPN algorithm exhibits delayed convergence and is limited by its fully connected architecture, which is unable to handle input and output data sets with different dimensions. This creates inconsistencies in its application instances and network size. Conversely, the RNN model suffers from issues such as Gradient disappearing and too much fitting.

The primary objective The goal of this study is to use neural network technology to look at data and networks in the optical transport network. Additionally, it aims to investigate the suitability of existing neural network models for this specific industry. Choose two distinct Two types of neural network models are BPN and RNN.,for training the data produced by the alarm dataset. Testing with real alarm and fault data shows that neural networks have an effect on where faults are located in the OTN model. During the experiment, we selected the commonly used evaluation indices, MSE and location time in the area of finding faults in optical networks. Additionally, we introduced the F1 score from statistics to provide in OTN, a more complete way to measure how well the neural network problem location monitor works. The test results show that the alarm data generated by the new optical transport network channel model is linked to the site of the fault and shows a temporal correlation. The RNN, especially the LSTM (long short-term memory) neural network, can deal with the problems of overfitting and gradient fading better than the traditional BP neural network. It also does a better job of finding problems in optical delivery networks than any other method.

Related Work:

Several research have examined ANN [8][9][10]. A neural network is a highly parallelized and distributed computing system consisting of a vast number of interconnected neurons, which serve as individual units for Processing of info. It possesses the attributes of autonomous finding out and autonomous adaptability. The system obtains information from the external world, namely from data sets, and constantly modifies the important weights between the neurons that are linked based on this information. The goal is to minimise the discrepancy between what was supposed to happen and what actually happened[11]. The neural network is taught with sets of data until the parameters are changed. significant weights achieves a condition of stability. An in-depth analysis is conducted on the use use of artificial neural networks in data gathering, as talked about in[12]. The ANN holds great potential for applications in data mining due to its remarkable flexibility, resilience, and distributed parallel processing capabilities. The author primarily focuses on analysing the architectural framework of the CNN as described in Reference[13][14]. Additionally, the author provides a comprehensive overview of the CNN's practical applications, including image classification, Among other things, it can recognise faces, get sounds, and find targets. The CNN's neighbourhood link, sharing weight, and pooling operations efficiently decrease network complexity, minimise training parameters, and provide a certain amount of resistance to scaling, translation, and distortion. The system exhibits high resilience and the capacity to withstand faults, while also being easily trainable and optimizable. However, CNN have a strong need for the dimension of input data, and they are unable to accomplish the intended training impact due to the lack of regularity and susceptibility to disturbances in the data. In reference[15], The author employed a BP neural network to achieve picture restoration. They created used the LM algorithm to teach and learn on a standard three-layer BP neural network[16][17]. Reference [18] presents a scene matching system that utilises a neural network and is based on the idea of fuzzy sets. How fuzzy sets are used exhibits superior resistance to interference compared to CNN algorithms. The paper referenced as [19] introduces gradient regularisation and Dropout approaches in picture description to prevent model overfitting. Additionally, the paper introduces the use of GRU to decrease how many factors were used to train the model.

Conversely, there is a plethora of interconnected studies in the realm of OTN fault localization. In reference [20], a method is suggested that utilises a combination of OCDR (Optical Coherence Domain Reflectometry) and OTDR (Optical Time Domain Reflectometry) to effectively monitor and pinpoint problems in all optical fibres and components inside a passive optical network. The mathematical theory described in Reference[21] is utilised to examine the issue of locating multiple faults in an optical network. The challenge of fault detection is transformed from from studying random events to studying events that aren't so clear-cut.

That being said, the fault membership function model must undergo extensive verification using a substantial amount of actual data. Additionally, the selected lattice OTN architecture is very uncomplicated. Multi-granularity optical channels make it hard to find problems in optical switching systems. To fix this problem, It is shown how a network works with channels. As explained in reference, the binary tree method is used to find faults in multi-granularity optical networks.[22]. Indeed, when the binary tree method encounters a substantial quantity of alert sets, it necessitates a significant amount of storage capacity. In reference [23], The author presents a technique for identifying a rapid fault connection known as a In a WDM network, an

m-trail is used for tracking. This method gets around the M-cycle's circular problems and provides a cheaper way to keep an eye on things than the M-cycle does. In relation to [24], It is shown how to use a neural network to find where problems are in WDM fibre networks. To set up and train the warning equipment set and fault equipment set, the standard BP neural network model is used. In any case, in the field of optical transport
The dimensions of the network, alert signal, and faulty equipment are not consistently set. The performance of BP neural networks deteriorates when dealing with longer sequences due to the limitations of their architecture. Simultaneously, In the configuration of the alarm equipment, the alert signal has a very important mapping relationship. Because of this, the BP neural network is not the best choice for analysing the warning signal. So, this dissertation tries to fill in the gaps by adding to the study that was done in Reference [25]. The channel-based network model is used to figure out what's wrong with the optical transport network.

3. Architecture of OTN

There are four steps that can be taken to make optical transport networks more survivable: fault recognition, fault location, fault notification, and fault recovery [26]. But in OTN, fault recovery can't happen until the problem is found and fixed. As a result, you need to find a good way to identify things quickly and accurately, as well as a fault recovery strategy that fits.

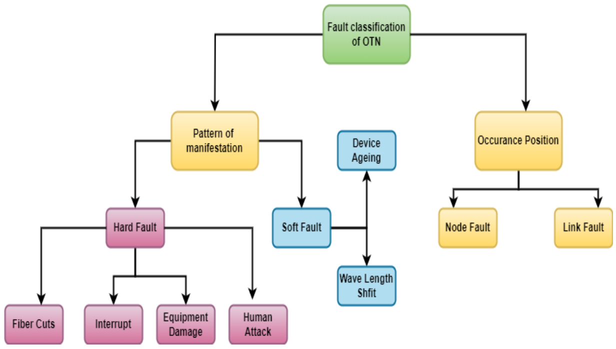

Fig. 1. Classification of Faults for OTN

Figure 1 illustrates that failure in OTN may be categorised into two types: both soft and hard faults, based on the distinct manifestations of faults. Network problems that cause a slowdown in performance are known as soft faults. In most cases, soft failures are difficult to detect, although they rarely affect network performance.A hard fault occurs when there is an interruption in the transmission channel, resulting in a total disruption of the transmission service due to a sudden incident. In the event of a severe network failure, prompt action must be taken to prevent significant data loss[27].
According on the defect's location, it can be categorised as either a node fault or a link fault [28]. Node failure mostly occurs due to equipment malfunctions, device power failures, single board disconnections, faults in a number of factors, including the optical transmitter.
Communication, service quality, devices, processing failure, and environment are the five main types of alarms that might occur in an optical transport network. [29]. The optical transport network fault detection procedure is the focus of this study since it is critical for finding network defects and getting the network back up and running.

4. Methodologies:

In this research work, we are working on fault detection in OTN. Figure 2 represents the overall system architecture of the proposed work. In this paper, we are predicting the faults as HF or SF.

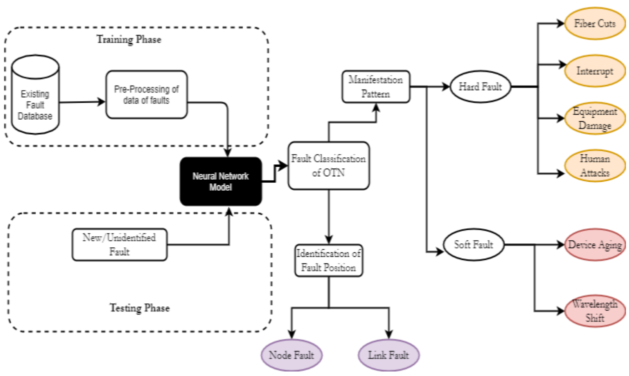

Fig. 2. System Architecture

4.1 Dataset Description and Pre-Processing:

The NSL-KDD dataset, widely utilised for IDS development [30], serves as the database for this study. This database is an improved iteration of the KDDCUP99, where duplicate records have been deleted to reduce bias. The NSLKDD dataset comprises KDDTrain+, which serves in place of the training set, and KDDTest+ for validation and KDDTest-21 for testing.

Significantly, the validation set lacks some defects that are included in the training set. Each record consists of a total of 41 features, with basic features ranging from 1 to 10, range of features for content from 11 to 22, and features for traffic from 23 to 41. The fault types may be classified into two categories: HF and SF. A preprocessing approach is utilised to improve the quality of the dataset and the performance of the classification. The collection consists of 41 characteristics, with 38 being integers and three that are not integers (kind of protocol, service, and flag). The probability density method is used to convert these non-numerical characteristics into numerical values. For example, the duration feature has a range of 0 to 58329, the src bytes and dst bytes features range from 0 to 1.3 × 109, and a handful of characteristics have a large discrepancy between their minimum and maximum values. As a result, these distances are reduced using logarithmic scaling, which are then fine-tuned using min-max normalisation to fall anywhere from 0 to 1.

4.2 Model Selection:

The CNN model [31] is comprised of many distinct layers. The input layer (IL) of the CNN receives the dataset with the CFS organised as one-dimensional input data. The convolutional layer (CL) is responsible for detecting features at various places in the input data. The filter is the layer's central component; it's a linear object that processes incoming data to generate an activation map. To improve learning convergence, the Rectified Linear Unit (ReLU) layer introduces nonlinearity to the data using a nonlinear activation function. In order to reduce computing complexity, the feature maps from the prior CL are subsampled using the Max-pooling Layer (MP). Achieving this is accomplished by determining the maximum responses within small, overlapping regions. A fully connected (FC) layer allows for high-level inference and subsequent nonlinear processing by coupling the output of the previous layer to every unit in the FC layer. An example of a convolutional layer using a one-by-one filter could be this layer.

A CNN's SoftMax (SM) layer, which is part of the OP, encodes the associated unit's probability distribution for a specific class. Assigning unique labels to the output, the output layer doubles as the classification layer in a classification context. A learning rate of 0.1, a momentum value of 0.9, and a regularisation value of 0.001 are the other typical parameters of the CNN model that have been set [32]. Furthermore, whereas the IL has dimensions of 33 × 1, the CL and MP both use 10 filters that measure 5 × 1.

5. Results and discussion:

In the binary classification job, all sorts of defects are classified as either hard faults or soft faults. By using With the help of our experts, we gathered 10,000 data sets. To ensure the CNN network model worked as expected, 1,000 data sets were selected as a test set, and 9,000 data sets were used as a training set. The CNN were trained and processed using the Kera's library in Python. The test sample was used to determine the mean square error and F1 score after 150 iterations. The test sample of the CNN achieves placement in 0.2151 seconds.

Figure 3 displays the curves of the square root of the error for the proposed CNN model. The graphic illustrates that the decline in the mean square error of the CNN model started to decelerate after 65 iterations. After 150 iterations, the mean square error reaches its minimum value.

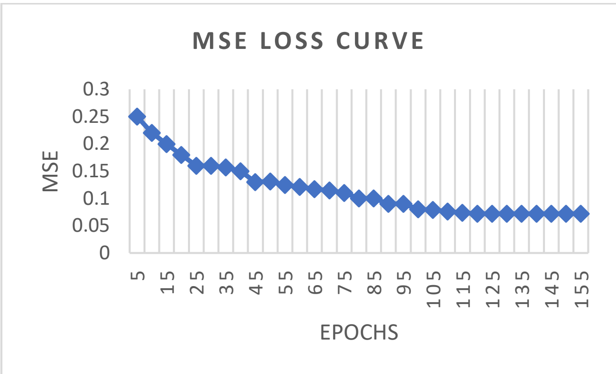

Fig. 3. MSE Loss Curve

Figure 4 plots the suggested CNN model's F1 score against time. After training is complete, the CNN's F1 score can be adjusted to 0.98. No. 85 is the sweet spot for convolutional neural networks (CNNs).

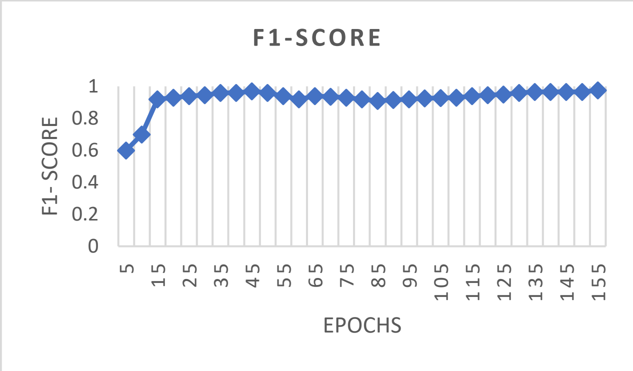

Fig. 4. F1-Score Graph

The architecture of the CNN neural network is intricate, with the possibility of recurring interactions between the three gates: input, output, and forget. The current design might benefit from simplification and enhancement. There must be a comprehensive evaluation of the augmented neural network's feasibility, nevertheless. For smaller networks, this approach is primarily employed in OTN at the moment. As a result, there will be fewer traffic demands and fewer wavelengths transmitted via the OTN link due to the limited number of channels in the network.

This approach is exclusively appropriate for a stationary network. If the network undergoes changes in size, for example, changes to the design of the network or shifts in the optical signal's wavelength throughout the link, it becomes imperative to re-evaluate and pick a new dataset for training the model.

6. Conclusion:

Fault classification in OTN is one of the most important tasks in today's scenario for smooth data transmission. Our work here proposes a CNN algorithm that gets the job done. using binary classification of faults in OTN. The CNN classifier performance was validated with testing data, and our proposed CNN model gives 98% as an F1-score. In the future, we will not only detect HF or SF, but we will also try to get further classifications like HF and SF, like fibre cut, interrupt, human attack, device aging, etc.

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