Network Digital Twin for Network Failure Classification using Deep Neural Network

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심층신경망을 이용한 네트워크 장애 분류를 위한 디지털 트윈 네트워크

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Abstract

Network failures significantly hinder the reliability and efficiency of communication infrastructure. Digital Twins (DTs), which are virtual representations of real-world networks, can be used to mimic and study network behavior. This work investigates the Deep Neural Networks (DNNs) for network failure classification using data from a Network Digital Twin (NDT). We propose a DNN-based model that leverages the extensive data collected from the NDT to distinguish and classify various types of network failures. Our proposed method tackles the imbalance problem and use a handcrafted method to classify the network failure based on five failure categories. Our experiment reveals that our proposed method can accurately classify network failure types. We train our results on NDT data and test the result with real network data.

Ⅰ. Introduction

Network failures cripple the dependability and effectiveness of communication infrastructure. To address this challenge, Digital Twins (DTs) offer a powerful solution. DTs are virtual replicas of real networks that can be used to simulate and analyze network behavior [1]. Recent advancements in network technologies, such as 5G, cloud-native capabilities, and network function virtualization, have revolutionized the telecommunications industry, delivering blazing-fast speeds to users [2]. These cutting-edge features position DTs as a key technology for the future of 6G. Research has explored the potential of DTs to optimize wireless communication performance for tasks like resource sharing, content caching, and compute offloading [3]. Moreover, modern Artificial Intelligence (AI) technologies offer a paradigm shift, allowing us to move beyond reactive fault management to proactive fault prediction, empowering operators to take preventative measures.

One machine learning approach is frequently used by currently suggested failure detection systems to detect or classify failures [4]. This presents several difficulties. First, one model usually does well in either classification or fault detection. The classification performance might be enhanced by combining several models, especially ones that have been trained for a particular job. Secondly, this one model has to receive and process all of the samples. If the network under observation is dispersed, this will result in elevated computational expenses and high bandwidth demands, ultimately causing a rise in latency. Finally, a lot of the time the suggested models are unable to identify classes of failure that are insignificant in the system.

Ⅱ. DNN Model for NDT Failure Classification

This approach utilizes a Deep Neural Network (DNN) for classifying network failures based on data collected from a Network Digital Twin (NDT). The datasets were part of the ITU challenge in 2023 [5].
Data preprocessing is crucial to ensure the DNN can effectively learn from the data. We use Min-Max scaling to scale all features to a common range to prevent specific features from dominating the learning process. Synthetic minority over-sampling techniques (SMOTE) were employed to create synthetic data points for the minority classes by interpolating between existing minority class data points. This helps balance the class distribution and allows the DNN to learn effectively from all failure categories.

There are three layers in the DNN model: input, hidden, and output. The preprocessed data is sent to the input layer, and the output layer generates the failure class prediction.

Let $X=(x_1, x_2, \cdots, x_d)$ be the input feature vector, where d is the number of features. The DNN model computes the output $\hat{y}$ as follows:

1. The input layer passes the features X to the first hidden layer.
2. Each hidden layer l computes a weighted sum of the inputs from the previous layer, applies a non-linear activation function σ, and passes the result to the next layer:

$$h^{(l)} = \sigma(W^{(l)}h^{(l-1)} + b^{(l)}) \quad (1)$$

Where $W^{(l)}$ and $b^{(l)}$ are the weight matrix and bias vector for layer l respectively.

3. The output layer computes the predicted class probabilities using a softmax activation function:

$$\hat{y}_k = \frac{e^{zk}}{\sum_{j=1}^{c} e^{zj}}, \ k = 1, 2, \cdots, C \quad (2)$$

Where C is the number of classes, and $z = W^{(l)}h^{(l-1)} + b^{(l)}$ is the weighted sum of the inputs from the last hidden layer $(l-1)$.

Ⅲ. Result and Discussion

The results show that the proposed DNN model achieves excellent performance in classifying network failures across all 16 classes. The precision, recall, and F1-score are consistently high, indicating the model's ability to accurately identify different failure types while minimizing false positives and false negatives. Both in Fig 1. and Fig. 2 The precision scores range from 0.92 to 1.00, with most classes achieving a perfect precision of 1.00. This means the model makes very few incorrect positive predictions, minimizing the risk of misclassifying non-failure instances as failures.

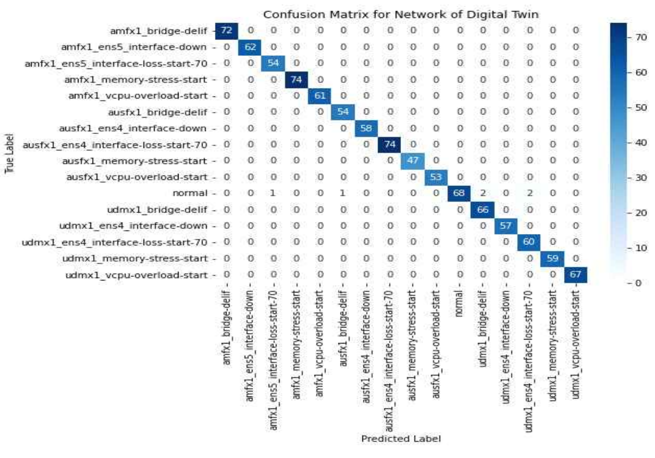

Figure 1. A confusion matrix for NDT classification

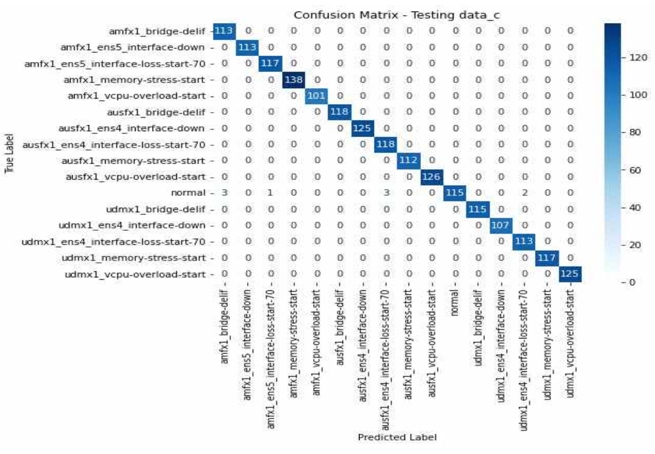

Figure 2. Confusion matrix for real network failure classification

Ⅳ. Conclusion

The study uses data from a Network Digital Twin (NDT) to show how well Deep Neural Networks (DNNs) classify network faults. Even in the presence of unbalanced data, the suggested DNN model can reliably identify different forms of network failure by utilizing the extensive data that the NDT has collected. This demonstrates how proactive network management and increased network resilience may be achieved with NDTs and DNNs. The technique's suitability for use in real-world situations is further confirmed by the effective training on NDT data and testing on actual network data.

ACKNOWLEDGMENT

This work was supported by Innovative Human Resource Developmen t for Local Intellectualization program through the Institute of Informat ion & Communications Technology Planning & Evaluation(IITP) grant funded by the Korea government(MSIT). (IITP-2024-00156287) and th is work was supported by the Institute of Information & communicatio ns Technology Planning & Evaluation(IITP) grant funded by the Kore a government(MSIT) (RS-2024-00345030, 디지털 트윈 기반 네트워크 장애예방 및 운영관리 자동화 기술 개발)

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