

Efficient Data-Driven Detection System for Power Cable Failure in Smart Grid

Cuiwei Peng¹, Zuju Huang², Huiwu Huang^{2*}, Jiahui Chen^{2*}

¹School of International Education

Guangdong University of Technology, Guangzhou 510006, China

²School of Computer Science and Technology

Guangdong University of Technology, Guangzhou 510006, China

vivianoop3@gmail.com, 3328047983@qq.com, hedy@gdut.edu.cn, csjhchen@gmail.com

*Corresponding author: Huiwu Huang, Jiahui Chen

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ABSTRACT.

Determining the remaining lifetime of power apparatuses is crucial for maintaining the availability of electric power during operation. One of the key components in power transmission and distribution is cross-linked polyethylene (XLPE) underground cables. While deep learning techniques have recently gained traction in distribution operations due to their impressive performance, predicting potential failures of power cables and implementing timely technical measures remains challenging. Traditional aging methods used in most diagnostic studies on medium voltage cables require extensive measurement durations. Moreover, the aging and failure of power cables are primarily caused by electrical, thermal, chemical, and physical stresses on the insulation material, with the probability and frequency of these stresses varying significantly. Consequently, collecting sufficient data to train an effective deep learning model is both difficult and time-consuming. In this paper, we present the comprehensive development of an innovative and autonomous deep learning-based failure prediction system for power cables. This system employs Generative Adversarial Networks (GANs) to generate necessary data from a limited source dataset and subsequently trains an LSTM or CNN on this augmented data. The trained model is then transferred to a target dataset containing limited data on the features and status of power cables. The proposed system was validated and compared with baseline models (LSTM or CNN). The test and evaluation results demonstrate that the proposed system outperformed the baseline models.

Keywords: Deep learning, Data expansion, Transfer learning, Power Cable Failure

1. Introduction. Monitoring electrical infrastructures is crucial for maintaining the continuous operation of industrial, commercial, and domestic activities. Ensuring the quality and stability of the power equipment has become a central focus in the study and development of smart grids, thereby opening new avenues in scientific research [1, 2]. Recently, cross-linked polyethylene (XLPE) cables as one of the key components in power transmission and distribution have become increasingly prevalent in power systems owing to their exceptional electrical and physicochemical properties [3]. In critical situations, the failure of a cable can result in millions of dollars in damage to consumers, utilities, and power grids. Thus, it is essential to carefully monitor potential failures and implement effective preventive measures [4]. In this study, a failure prediction system for XLPE cables was provided.

Medium voltage (MV) cables are equipment where failures are frequently encountered, and their installation costs are notably high. Predicting the remaining lifetime of the cables is crucial for maintaining the availability of electric power during operation. However, accurately predicting the remaining life of electrical equipment installed and operated in the field poses significant challenges. Most dielectric diagnosis studies for assessing the performance of power cables rely on aging methods that necessitate lengthy measurement durations [5]. Moreover, given that medium voltage (MV) cables are typically buried underground and challenging to inspect, it is imperative to accurately pinpoint malfunctions and intervene in the most critical areas [6]. In the literature, predicting methods used to utilize historical data of cable failure or condition monitoring records [7, 8, 9]. However, acquiring sufficient historical data is essential for ensuring prediction accuracy, which often entails significant costs due to the aforementioned challenges.

In this paper, we present a novel approach to address this challenge. We aim to develop an efficient and intelligent deep learning-based system for predicting failures in electric cables. Our system is designed to effectively utilize a limited amount of historical data while achieving high performance. Specifically, our contributions are summarized as follows:

- We propose a novel deep learning-based failure prediction system for power cables that leverages a Generative Adversarial Network (GAN) for data augmentation. This approach allows the system to utilize a small-sized source dataset to generate sufficient data for training an effective prediction model. This method addresses the high cost associated with acquiring sufficient data in this field.
- Following training on the generated dataset, the prediction model in the proposed system is further refined using a target dataset. Given that the source dataset and the target dataset contain condition records for different types of cables, the system can adapt by utilizing any available source dataset with similar features. This adaptability enhances the system's flexibility and applicability across various datasets and cable types.
- Compared to the baseline models (LSTM or CNN) that are trained directly on the target dataset for failure prediction, the proposed system demonstrates superior performance.

The remaining sections are organized as follows. In Section 2, we review related research on cable failure prediction. Section 3.1 provides an overview of the data used for power cable failure detection. In Section 3, we describe the proposed system in detail. Section 4 presents the evaluation of the proposed system. Finally, Section 5 offers a summary of the proposed system.

2. Related work. In the literature, figuring out what factors are significant in cable failures is important. Tang et al. proposed a statistical model to analyze the early-failure data associated with power cables [10] in 2013. It accurately identified significant factors, such as a specific manufacturer or installation method, that may contribute to cable failures. In 2015, Sachan et al. provided a method which is an amalgamation of two models to predict failure for XLPE cables [11]. They classified the cause of cable failures into two types: ageing effects and random causes like sudden shock. Thus, they used two different models to predict different failures respectively. Recently, deep-learning-based methods have gained prominence in cable diagnostics [12, 13, 14]. Results from these approaches demonstrate their effectiveness in accurately diagnosing and identifying defects in cables. However, a significant challenge for these methods is obtaining sufficient data for training, as collecting real aging and failure data for power cables incurs substantial costs.

For power cable failure detection, CNNs (Convolutional Neural Networks [15]) have been used to analyze time-series data and signal waveforms from power cables to identify

and locate faults. For instance, Wang et al., 2019 demonstrated the use of CNNs for automatic fault detection in power distribution networks. RNNs (recurrent neural networks), particularly Long Short-Term Memory (LSTM) networks [16], are effective in processing sequential data and have been applied to predict and detect faults based on historical power cable data. These models leverage the feature extraction capability of CNNs and the temporal pattern recognition ability of RNNs to enhance fault detection. Liu et al. [17] combined CNN and LSTM networks to accurately detect cable faults. Said et al. [18] address the critical need for reliable fault detection and location systems for underground power cables in nuclear facilities. Given the high stakes associated with nuclear power systems, ensuring the integrity and functionality of power cables is paramount. The paper presents a deep learning-based approach to accurately classify and locate faults in these cables, aiming to enhance the safety and reliability of nuclear facilities. Sampedro et al. [19] explore applying deep learning techniques for automatically recognizing and diagnosing electrical insulator strings. Electrical insulators are critical components in power transmission systems, and their failure can lead to significant power outages and maintenance costs. This paper aims to develop a deep learning-based system that can automatically identify and diagnose faults in insulator strings, enhancing the reliability and efficiency of power transmission networks. Hu et al. [20] focus on developing a deep learning-based fault diagnosis algorithm aimed at preventing protection malfunctions in electrical power systems. Protection systems are critical for ensuring the safety and reliability of power grids, and malfunctions in these systems can lead to severe consequences, including widespread outages and equipment damage. The proposed algorithm seeks to enhance the fault diagnosis process, thereby reducing the risk of protection system failures. Khaleghi et al. [21] address the critical issue of detecting load redistribution attacks in smart grids, which can lead to cascading failures and severe disruptions in power systems. These attacks exploit the vulnerabilities in load distribution, potentially causing widespread power outages. They propose a deep learning-based detection mechanism to identify such attacks and mitigate the risk of cascading failures.

3. System Modeling. As illustrated in Figure 1, the framework of the proposed system comprises data preprocessing, data augmentation, and transfer learning. Initially, all data undergo normalization. Subsequently, a source dataset with features similar to those of the target dataset is identified. By training a Generative Adversarial Network (GAN) on the source dataset, we generate sufficient samples to train a power cable failure prediction model. The prediction model is first trained on the augmented dataset and then fine-tuned using the target dataset.

3.1. Data Preprocessing. The proposed system utilizes two datasets. The first is the 20KV cross-linked polyethylene (XLPE) Underground Cable Inspection Dataset [22], which is employed to train the generative network and generate new data for subsequent components of the system. For simplicity, we refer to this as the source dataset. The second is the 15KV XLPE Underground Cable Inspection Dataset [23], used to train the prediction model in the final stage of the system, and referred to as the target dataset. The target dataset consists of data specifically related to the cables whose health conditions we aim to predict. In contrast, a source dataset can be any dataset with features similar to those of the target dataset. For example, a 25KV XLPE Underground Cable Inspection Dataset could also serve as a source dataset.

The two datasets are provided by the Utility Analytics Network, an organization dedicated to sharing data and promoting research and application of utility data analytics for North American utility companies. The source dataset contains 3,943 cable segments,

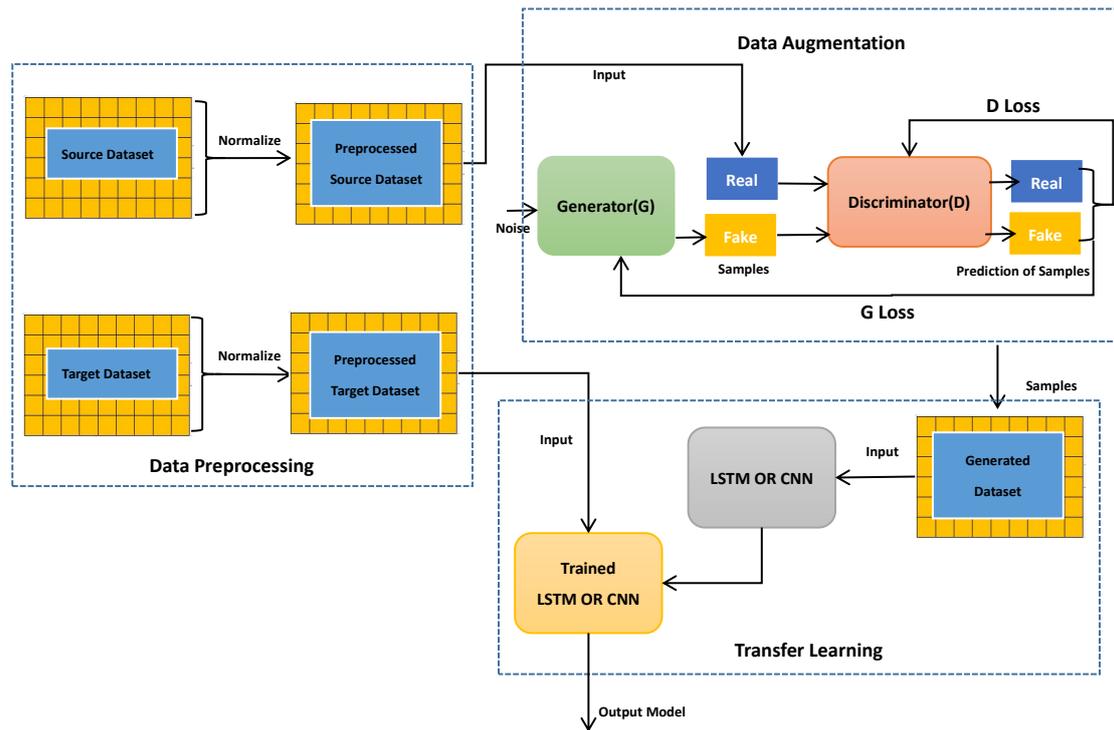


FIGURE 1. Framework of the proposed system

each with four condition features. We selected the inspection records for these cables from 2017, resulting in a dataset with dimensions of (3, 943, 4). This indicates that the source dataset includes 3, 943 records, each with 4 features. Similarly, the target dataset has dimensions of (2, 500, 4), signifying 2, 500 records, each with 4 features. Both datasets are relatively small in size for deep learning applications. Since the features in both the source dataset and target dataset are numerical, we normalize the data for machine learning.

3.2. Data Augmentation. In the realm of machine learning, Generative Adversarial Networks (GANs) [24] have emerged as a powerful tool for data augmentation. GANs are a class of artificial intelligence algorithms used in unsupervised learning to generate new data samples. In the proposed system, a GAN is implemented to expand the dataset, thereby enhancing the diversity of data available for training the power cable failure prediction model.

The GAN operates on a unique principle involving two neural networks: the generator (G) and the discriminator (D), which engage in a continuous game of competition. The generator aims to produce data that is indistinguishable from real data, while the discriminator strives to accurately differentiate between the generator's fake data and actual data. This adversarial process leads to the improvement of both networks over time, with the generator creating increasingly convincing data and the discriminator becoming more adept at detection. The key components of the GAN are as follows:

1. Generator's Objective : The generator tries to minimize the following loss function:

$$\min_G \log(1 - D(G(z)))$$

where z is a random noise vector sampled from a latent space, and $G(z)$ is the data generated by the generator.

2. Discriminator's Objective : The discriminator attempts to maximize its probability of correctly classifying both real and fake data:

$$\max_D [\log D(x) + \log(1 - D(G(z)))]$$

where x represents real data, and $D(x)$ is the probability that x is real as determined by the discriminator.

3. Adversarial Loss : This is the loss function that both networks aim to optimize from their respective perspectives:

$$\min_G \max_D = \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$

where $p_{\text{data}}(x)$ is the data distribution of real data, and $p_z(z)$ is the distribution of the generator's input noise.

The training of the GAN involves alternating between optimizing the discriminator to maximize its accuracy in distinguishing real from fake data and optimizing the generator to produce data that is increasingly difficult for the discriminator to classify as fake. This adversarial training process continues until the generator produces data that is nearly indistinguishable from real data, at which point the discriminator's performance plateaus, indicating that the GAN has been effectively trained. The beauty of this approach lies in its ability to generate new, synthetic data that can be remarkably similar to the original dataset, thus providing a means for data augmentation in scenarios where data is scarce or needs diversification.

3.3. Transfer Learning. After data augmentation, we employ a powerful technique known as transfer learning [25] within the field of deep learning. Transfer learning involves reusing a pre-trained model on a new, but related problem. The essence of transfer learning lies in its ability to leverage the knowledge gained from one task to enhance generalization on another task. In the proposed system, we utilize a model that has been trained on the large, generated dataset and then fine-tune it with the target dataset for the power cable failure prediction task. This approach is particularly advantageous given the small size of the target dataset.

We test two well-known models within the proposed system, though these models can be replaced with any other suitable deep learning models, enhancing the system's adaptability. The models we used are as follows:

LSTM (Long Short-Term Memory): LSTM [16] is a type of recurrent neural network (RNN) adept at learning long-term dependencies. The essential equations governing the LSTM's cell state and hidden state updates are:

$$\begin{aligned} f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\ i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \\ C_t &= f_t * C_{t-1} + i_t * \tilde{C}_t \\ o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t * \tanh(C_t) \end{aligned}$$

where f_t is the forget gate's activation vector, i_t is the input/update gate's activation vector, \tilde{C}_t is the cell input activation vector, C_t is the cell state vector, o_t is the output gate's activation vector, h_t is the hidden state vector, W and b are the weights and biases for different gates, σ is the sigmoid function, and \tanh is the hyperbolic tangent function.

CNN (Convolutional Neural Network): The CNN [15] model relies on convolution and pooling operations. The convolution operation for a single dimension is described as:

$$S(i) = (K * X)(i) = \sum_{a=-\infty}^{+\infty} K(a) \cdot X(i - a)$$

Where $S(i)$ is the output of the convolution, K is the filter, X is the input, $*$ denotes the convolution operation. The pooling operation, specifically max pooling, is described as:

$$P(j) = \max(X(j \cdot s : j \cdot s + f))$$

Where $P(j)$ is the output of the pooling operation, X is the input, s is the stride, f is the pooling size. These operations are applied sequentially in the CNN model, combined with ReLU activation functions and fully connected layers to produce the final output. The ReLU function is defined as:

$$ReLU(x) = \max(0, x)$$

The LSTM model processes sequences, maintaining a hidden and cell state, whereas the CNN model applies convolutions and pooling to extract features from sequence data. Both models conclude with fully connected layers to map the extracted features to the desired output size.

4. Experiment and Discussion.

4.1. Experiment Environment. We assessed the proposed system alongside well-known models on a multi-user computing platform. This platform features 15 Intel(R) Xeon(R) E5-2620 V4 CPUs running at 1.20GHz, 2 Tesla P100 PCIe 16GB GPUs, and approximately 111.8 GB of available memory. It operates on CentOS Linux 7 (Core). The system was developed using Python, utilizing libraries such as sklearn, pandas, and torch.

4.2. System Evaluation Metrics. In the experiment, we try to predict a health condition score which indicates whether a power cable is still reliable and gives a potential failure warning. Thus, this is a regression problem and the metrics which are usually used to evaluate the performance of a deep-learning model in this scenario are as follows:

1. Mean Squared Error (MSE): MSE measures the average squared difference between the actual and predicted values. A lower MSE indicates better model performance, with a value of 0 representing perfect predictions. However, because it squares the errors, MSE is sensitive to outliers and can give a distorted view if large errors are present. The formula for calculating this metric is as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

where y_i represents the actual value of the dependent variable for the i^{th} observation in your dataset and \hat{y}_i denotes the predicted value for the i^{th} observation, which is output by the regression models.

2. Mean Absolute Error (MAE): MAE calculates the average absolute difference between the actual and predicted values. It's less sensitive to outliers compared to MSE and provides a straightforward measure of prediction accuracy. A smaller MAE suggests a model that predicts more closely to the actual values. The formula for calculating this metric is as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

3. R-squared (Coefficient of Determination): R-squared quantifies the proportion of the variance in the dependent variable that is predictable from the independent variables. Usually, it ranges from 0 to 1, with higher values indicating a better fit of the model to the data. In our experiment, we will see a negative R-squared value in a regression model without expanding the training data. This typically indicates that the model fits the data worse than a simple horizontal line, or mean-based model. An R-squared of 1 means the model explains all the variability of the response data around its mean. The formula for calculating this metric is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

where \bar{y} is the mean (average) of the actual values y of the dependent variable across all observations in the dataset.

4. Median Absolute Error (MedAE): This is a robust metric used to evaluate the performance of regression models, particularly in deep learning. MedAE is the median of all absolute differences between the predicted values and the actual target values. It's a measure of the typical error size. A lower MedAE value indicates that the median error is small, and hence, the model's predictions are generally close to the actual values. The best possible value is 0.0, which would mean that at least half of the predictions are exactly correct. The formula for calculating this metric is as follows:

$$MedAE = \text{median}(|y_i - \hat{y}_i|)$$

4.3. Tuning Hyperparameters. The deep learning processes in the proposed system include data augmentation via a Generative Adversarial Network (GAN) and transfer learning utilizing LSTM or CNN models. To compare these processes with the baseline models—LSTM or CNN applied directly without data augmentation—we employ identical hyperparameters for the LSTM or CNN in both the transfer learning and baseline scenarios. Consequently, this section concentrates on the hyperparameters involved in the data augmentation process. Specifically, the following hyperparameters are crucial for the configuration and training:

1. Number of Samples for data augmentation: The optimal number of samples for data augmentation can vary significantly depending on the specific task, the complexity of the model, and the original dataset size. In our experiment, we utilized two datasets described in Section 3.1, referred to as the source dataset and the target dataset. To assess the impact of sample size on performance, we increased the number of samples in multiples of the target dataset's size. As illustrated in Figure 2, the system achieved higher performance when the number of samples was approximately seven times the size of the target dataset.

2. Number of Epochs: This indicates the number of complete passes through the source dataset when training the Generative Adversarial Network (GAN). As illustrated in Figure 3, the system achieved higher performance when the number of epochs was approximately 150.

3. Latent Vector Size: The latent vector size, also known as the noise dimension, in a Generative Adversarial Network (GAN) is an important hyperparameter that defines the dimensionality of the space from which random inputs are sampled to generate data. A larger latent vector size can potentially capture more nuances and variations in the data, leading to more diverse and high-quality generated samples. Conversely, a smaller latent vector size may result in less diversity but can be easier to train and less prone to overfitting. As illustrated in Figure 4, we chose 10 for this parameter to get a good performance.

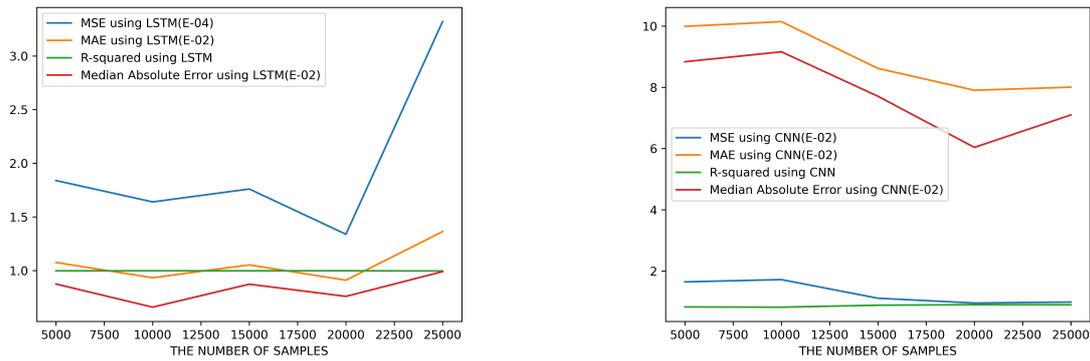


FIGURE 2. Different Number of Samples

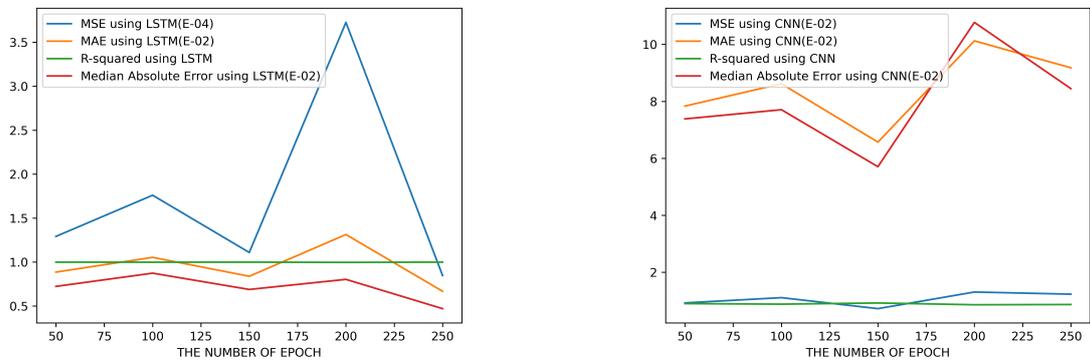


FIGURE 3. Different Number of Epochs

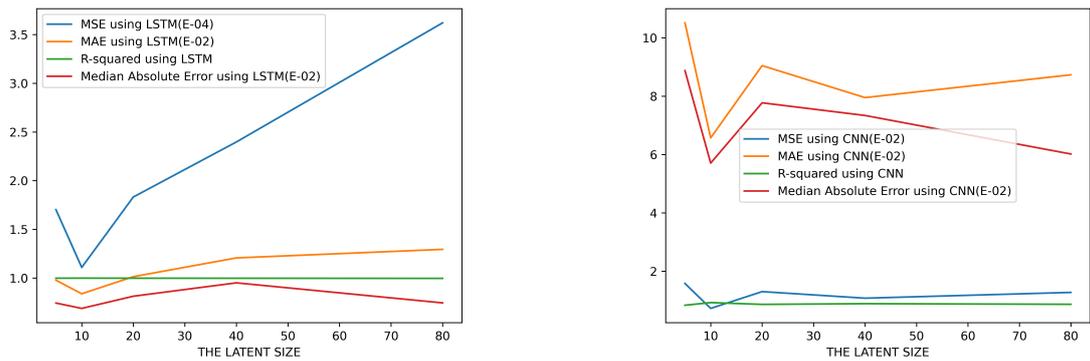


FIGURE 4. Different Latent Size

4. Batch Size: The batch size specifies the number of training samples to be processed before the model’s internal parameters are updated. As illustrated in Figure 5, the performance curves for both LSTM and CNN models in transfer learning exhibit two distinct valleys. This suggests that the optimal batch sizes are approximately 32 or 64.

5. Learning Rate: The learning rate in Generative Adversarial Networks (GANs) is a critical hyperparameter that significantly affects the training dynamics and stability of both the generator and discriminator. We optimized the learning rates for the discriminator and generator independently. As depicted in Figure 6, the performance curves

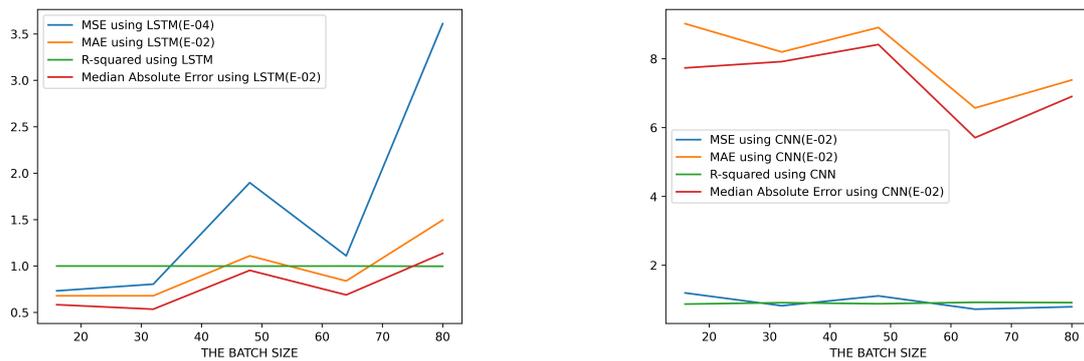


FIGURE 5. Different Batch Size

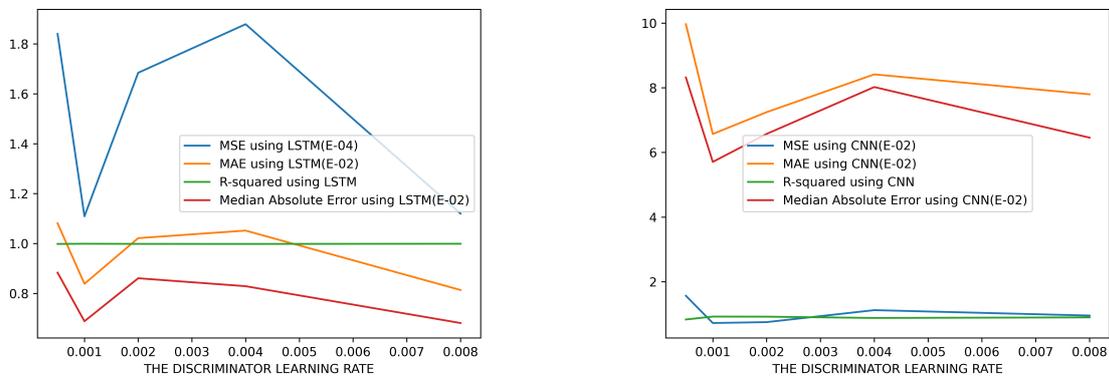


FIGURE 6. Different Discriminator Learning Rate

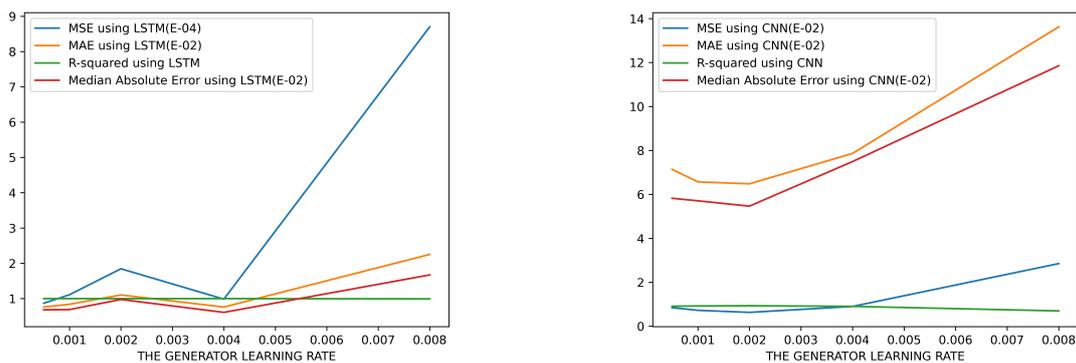


FIGURE 7. Different Generator Learning Rate

indicate that the optimal discriminator learning rates are approximately 0.001 or 0.008. Similarly, Figure 7 shows that the best generator learning rates are 0.001 and 0.004 when using the LSTM model for transfer learning. However, with the CNN model, performance deteriorates as the generator learning rate increases.

4.4. Comparison. To compare with the baseline models—LSTM or CNN, we employ identical hyperparameters for the LSTM or CNN in both the proposed transfer learning and baseline scenarios. As is shown in Tables 1 and 2, the comparison is taken using two

TABLE 1. COMPARISON WITH %10 TEST SIZE

Models	MSE	MAE	R-squared	MedAE
Our system with LSTM	0.0286×10^{-2}	1.4517×10^{-2}	99.7479×10^2	1.3148×10^{-2}
LSTM	0.1381×10^{-2}	2.7587×10^{-2}	98.7810×10^2	1.7436×10^{-2}
Our system with CNN	1.0306×10^{-2}	7.5009×10^{-2}	85.9351×10^2	5.9098×10^{-2}
CNN	7.0259×10^{-2}	23.2604×10^{-2}	4.1121×10^2	22.2546×10^{-2}

TABLE 2. COMPARISON WITH %30 TEST SIZE

Models	MSE	MAE	R-squared	MedAE
Our system with LSTM	0.0754×10^{-2}	2.2703×10^{-2}	99.3039×10^2	2.1553×10^{-2}
LSTM	0.4251×10^{-2}	5.7583×10^{-2}	96.0759×10^2	5.4046×10^{-2}
Our system with CNN	1.1305×10^{-2}	8.7939×10^{-2}	85.9831×10^2	7.5667×10^{-2}
CNN	8.2874×10^{-2}	24.7622×10^{-2}	-2.7525×10^2	22.35×10^{-2}

sizes of the target dataset. %10 test size means %90 of the target dataset are used for training and %10 are for evaluation. Generally, the performance of the proposed system is better than the baseline models in all the evaluation metrics. We can find that the lack of data for training in the CNN model will get worse than that in the LSTM model. When the test size is %30 as is shown in Table 1, the value of R-squared for the baseline CNN model becomes negative, indicating that the model fits the data worse than a simple horizontal line.

5. Conclusion. In this study, we proposed, developed, tested, and validated an efficient and intelligent deep learning-based failure prediction system for electric cables in power transmission and distribution. The system development was structured into three main components: data preprocessing, data augmentation, and transfer learning. Utilizing a GAN-based design allowed the system to generate sufficient effective data for training, significantly enhancing prediction performance. Furthermore, to provide a comprehensive evaluation of the system's performance, we employed a range of metrics including Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared, and Median Absolute Error (MedAE). The experimental results demonstrated that the proposed system outperformed the baseline deep learning models in this domain. To extend this research, several recommendations for future work can be considered:

1. Advanced GAN Architectures. Investigating the use of more advanced GAN architectures or hybrid models to further enhance the quality and variety of generated data.

2. Multi-Modal Data Integration. Combining electrical, thermal, chemical, and physical data with existing datasets to capture a more comprehensive view of cable health and potential failure mechanisms.

3. Longitudinal Studies. Conducting longitudinal studies to assess the long-term performance and reliability of the prediction system under varying operational conditions.

By addressing these recommendations, future research can build on the foundations laid by this study, leading to even more accurate and reliable failure prediction systems for power transmission and distribution networks.

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REFERENCES

- [1] A. E. L. Rivas and T. Abrao, "Faults in smart grid systems: Monitoring, detection and classification," *Electric Power Systems Research*, vol. 189, p. 106602, 2020.
- [2] N. Bhusal, M. Abdelmalak, M. Kamruzzaman, and M. Benidris, "Power system resilience: Current practices, challenges, and future directions," *Ieee Access*, vol. 8, pp. 18 064–18 086, 2020.
- [3] J. Wu, A. R. Mor, and J. J. Smit, "The effects of superimposed impulse transients on partial discharge in xlpe cable joint," *International Journal of Electrical Power & Energy Systems*, vol. 110, pp. 497–509, 2019.
- [4] Y. Chen, B. Hui, Y. Cheng, Y. Hao, M. Fu, L. Yang, S. Hou, and L. Li, "Failure investigation of buffer layers in high-voltage xlpe cables," *Engineering Failure Analysis*, vol. 113, p. 104546, 2020.
- [5] O. Arikan, C. C. Uydur, and C. F. Kumru, "Prediction of dielectric parameters of an aged mv cable: A comparison of curve fitting, decision tree and artificial neural network methods," *Electric Power Systems Research*, vol. 208, p. 107892, 2022.
- [6] I. Aizenberg, R. Belardi, M. Bindi, F. Grasso, S. Manetti, A. Luchetta, and M. C. Piccirilli, "Failure prevention and malfunction localization in underground medium voltage cables," *Energies*, vol. 14, no. 1, p. 85, 2020.
- [7] A. Zaeni, U. Khayam, and D. Viviantoro, "Methods for remaining life prediction of power cable based on partial discharge and cable failure history data," in *2019 International Conference on Electrical Engineering and Informatics (ICEEI)*. IEEE, 2019, pp. 662–665.
- [8] D. J. Jabha, K. Selvi, and R. Joselin, "A new approach for the failure prediction in xlpe power cables using acoustic emission technique," *International Journal of Electrical Power & Energy Systems*, vol. 81, pp. 336–345, 2016.
- [9] G. Li, Z. Wang, R. Lan, Y. Wei, Y. Nie, S. Li, and Q. Lei, "The lifetime prediction and insulation failure mechanism of xlpe for high-voltage cable," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 30, no. 2, pp. 761–768, 2022.
- [10] Z. Tang, C. Zhou, W. Jiang, W. Zhou, X. Jing, J. Yu, B. Alkali, and B. Sheng, "Analysis of significant factors on cable failure using the cox proportional hazard model," *IEEE Transactions on Power Delivery*, vol. 29, no. 2, pp. 951–957, 2013.
- [11] S. Sachan, C. Zhou, G. Bevan, and B. Alkali, "Failure prediction of power cables using failure history and operational conditions," in *2015 IEEE 11th International Conference on the Properties and Applications of Dielectric Materials (ICPADM)*. IEEE, 2015, pp. 380–383.
- [12] Y. Huo, G. Prasad, L. Lampe, and V. C. Leung, "Advanced smart grid monitoring: Intelligent cable diagnostics using neural networks," in *2020 IEEE International Symposium on Power Line Communications and its Applications (ISPLC)*. IEEE, 2020, pp. 1–6.
- [13] G. Heiler, T. Gadermaier, T. Haider, A. Hanbury, and P. Filzmoser, "Identifying the root cause of cable network problems with machine learning," *arXiv preprint arXiv:2203.06989*, 2022.
- [14] S. J. Chang and G.-Y. Kwon, "Anomaly detection for shielded cable including cable joint using a deep learning approach," *IEEE Transactions on Instrumentation and Measurement*, 2023.
- [15] K. O'shea and R. Nash, "An introduction to convolutional neural networks," *arXiv preprint arXiv:1511.08458*, 2015.
- [16] Y. Yu, X. Si, C. Hu, and J. Zhang, "A review of recurrent neural networks: Lstm cells and network architectures," *Neural computation*, vol. 31, no. 7, pp. 1235–1270, 2019.
- [17] X. Liu, D. Huang, T. Jing, and Y. Zhang, "Detection of ac arc faults of aviation cables based on hiw three-dimensional features and cnn-lstm neural network," *IEEE Access*, vol. 10, pp. 106 958–106 971, 2022.
- [18] A. Said, S. Hashima, M. M. Fouda, and M. H. Saad, "Deep learning-based fault classification and location for underground power cable of nuclear facilities," *Ieee Access*, vol. 10, pp. 70 126–70 142, 2022.
- [19] C. Sampedro, J. Rodriguez-Vazquez, A. Rodriguez-Ramos, A. Carrio, and P. Campoy, "Deep learning-based system for automatic recognition and diagnosis of electrical insulator strings," *IEEE Access*, vol. 7, pp. 101 283–101 308, 2019.
- [20] J. Hu, Z. Liu, J. Chen, W. Hu, Z. Zhang, and Z. Chen, "A novel deep learning-based fault diagnosis algorithm for preventing protection malfunction," *International Journal of Electrical Power & Energy Systems*, vol. 144, p. 108622, 2023.
- [21] A. Khaleghi, M. S. Ghazizadeh, and M. R. Aghamohammadi, "A deep learning-based attack detection mechanism against potential cascading failure induced by load redistribution attacks," *IEEE Transactions on Smart Grid*, vol. 14, no. 6, pp. 4772–4783, 2023.

- [22] Analytics, “Source dataset,” <https://www.kaggle.com/datasets/utilityanalytics/test-dataset>, 2020, accessed: 2024-03-28.
- [23] K. Analytics, “Target dataset,” <https://www..com/datasets/utilityanalytics/utility-underground-cable-dataset1>, 2020, accessed: 2024-03-28.
- [24] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, “Generative adversarial nets,” *Advances in neural information processing systems*, vol. 27, 2014.
- [25] F. Zhuang, Z. Qi, K. Duan, D. Xi, Y. Zhu, H. Zhu, H. Xiong, and Q. He, “A comprehensive survey on transfer learning,” *Proceedings of the IEEE*, vol. 109, no. 1, pp. 43–76, 2020.