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A Comparative Analysis of Deep Learning Models for Predicting Power System Failures

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Abstract: Power systems are critical infrastructure that face significant challenges due to increasing demand and inherent complexity. Predicting failures in power systems is crucial for enhancing grid reliability, minimizing downtime, and optimizing maintenance processes. This study evaluates various deep learning models, specifically convolutional neural networks (CNN), recurrent neural networks (RNN), and transformer models, for predicting power system failures. By analyzing these models' performance metrics on historical power grid data, the study provides insights into the strengths and weaknesses of each approach. The findings contribute to the development of more robust predictive models for power system reliability.

Keywords: Deep learning, power system failures, convolutional neural networks, recurrent neural networks, transformers, predictive modeling

1. INTRODUCTION

Power systems form the backbone of modern infrastructure, supporting critical services and enabling economic activity. However, the reliability of these systems is increasingly strained by aging infrastructure, growing demand, and the need for more resilient grids. Accurate predictive models are essential for forecasting system failures, enabling proactive maintenance, and ensuring consistent service delivery.

This study investigates the application of deep learning models in predicting power system failures. We focus on CNNs, RNNs, and transformer models due to their proven effectiveness in handling time-series data and complex features. By conducting a comparative analysis, we aim to highlight which model offers superior performance for failure prediction in power systems.

2. LITERATURE REVIEW

Deep learning has advanced predictive modeling in numerous fields, including healthcare, finance, and engineering. In power systems, traditional methods often rely on statistical models, which may not capture the complexity of large datasets or the temporal dependencies needed for accurate prediction. Recent studies demonstrate the value of deep learning models in capturing intricate patterns in power system data. For instance:

a. CNNs have been effective in handling spatial data and extracting features from grid structures.
b. RNNs, especially Long Short-Term Memory (LSTM) networks, address temporal dependencies in sequential data.

c. Transformers, with their attention mechanisms, provide high accuracy in complex, time-sensitive applications.
d. The review draws on previous research, showing the evolving focus from simpler models to more sophisticated architectures for enhancing prediction accuracy and computational efficiency.

3. METHODOLOGY

Data Collection

Historical power grid data was obtained from multiple sources, including SCADA systems and open-source power system repositories. The data was preprocessed to address missing values, outliers, and normalization.

Model Architecture

Convolutional Neural Network (CNN): CNNs were used for capturing spatial relationships within the grid data, focusing on regions with high failure probabilities.

Recurrent Neural Network (RNN) with LSTM cells: RNNs with LSTM units were implemented to handle the sequential nature of failure prediction data, preserving long-term dependencies.

Transformer Model: Transformer architectures were employed due to their robustness in learning long-term dependencies with higher efficiency in large datasets.

Performance Metrics

Models were evaluated based on accuracy, F1 score, precision, recall, and computational efficiency.

4. RESULTS AND DISCUSSION

CNN Performance

The CNN model showed significant accuracy in identifying grid regions prone to failure, leveraging spatial feature extraction. However, its prediction capacity was limited in capturing long-term dependencies across temporal sequences.

RNN with LSTM Performance

RNN models with LSTM cells performed well with sequential data, especially in time-sensitive failure prediction. The drawback was increased computational demand and susceptibility to vanishing gradient problems in longer sequences.

Transformer Model Performance

The transformer model outperformed the other architectures, particularly in balancing accuracy and computational efficiency. Its attention mechanism allowed it to focus on critical parts of the data, capturing long-term dependencies effectively without the need for recurrence.

5. CONCLUSION AND FUTURE WORK

The study highlights the transformer model's potential in predicting power system failures due to its efficiency and accuracy in managing complex temporal dependencies. Future research should focus on hybrid models combining CNNs and transformers to enhance spatial-temporal feature extraction. Moreover, more extensive datasets and domain-specific optimizations could further improve prediction accuracy.

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