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딥 러닝을 통해 스마트 그리드 이상 탐지 기능 강화

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Enhancing Smart Grid Anomaly Detection Through Deep Learning

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요 약

스마트 그리드로의 전력망 현대화는 효율성, 신뢰성, 지속 가능성 측면에서 많은 이점을 제공합니다. 그러나 복잡하고 상호 연결된 스마트 그리드 시스템은 이상 탐지와 그리드 회복력 유지에 있어 새로운 과제를 제시한다. 기존의 이상 탐지 방법은 스마트 그리드 데이터의 동적이고 이질적인 특성에 적응하기 어려워, 이상 탐지 및 완화에 있어 비효율성을 초래한다. 이러한 문제를 해결하기 위해 본 연구는 TensorFlow 프레임워크를 활용한 딥러닝 기술을 통해 스마트 그리드 이상 탐지와 회복력을 향상하는 새로운 접근 방안을 제안한다. 연구의 목표는 두 가지로 나뉜다. 첫째, 스마트 그리드 데이터 내에서 이상을 정확하게 감지할 수 있는 고급 딥러닝 모델을 개발하고, 둘째, 감지된 이상에 대해 선제적으로 대응하고 이를 완화하여 그리드 회복성을 강화하는 것이다.

ABSTRACT

Modernizing the power grid to a smart grid offers many benefits in terms of efficiency, reliability, and sustainability. However, complex and interconnected smart grid systems present new challenges in detecting anomalies and maintaining grid resilience. Existing anomaly detection methods have difficulty adapting to the dynamic and heterogeneous characteristics of smart grid data, resulting in inefficiency in anomaly detection and mitigation. To solve these problems, this study proposes a new approach to improve smart grid anomaly detection and resilience through deep learning technology using the TensorFlow framework. The goals of the research are divided into two. First, to develop an advanced deep learning model that can accurately detect anomalies within smart grid data, and second, to strengthen grid resilience by proactively responding to and mitigating detected anomalies.

키워드

Smart Grid Stability, Anomaly Detection, CNNs, Predictive Modeling, RNNs, Fault Detection
스마트 그리드 안정성, 이상 탐지, 합성곱 신경망, 예측 모델링, 순환 신경망, 고장 탐지

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Ⅰ. Introduction

The change of traditional power grids into smart grids shows an important leap forward in the realm of energy infrastructure. Smart grids leverage advanced technologies such as sensors, communication networks, and data analytics to improve the efficiency, reliability, and sustainability of electricity delivery systems. By enabling bidirectional communication and real-time monitoring of grid operations, smart grids empower utilities, consumers, and regulators to make informed decisions, optimize energy usage, and respond effectively to changing demand patterns and environmental factors. However, the transition to smart grids introduces new complexities and challenges, particularly in the domain of anomaly detection and grid resilience. Unusual anomalous behavior in the smart grid can result from various factors, such as abnormal consumption patterns by users, faulty grid infrastructure, system outages, cyber-attacks, or instances of energy theft[1-5].

Anomalies, which encompass a wide range of unexpected events or deviations from normal operating conditions, can have profound impacts on grid stability, service quality, and cybersecurity. These anomalies may arise from various sources, including equipment malfunctions, cyber-attacks, natural disasters, and changes in consumer behaviour. Traditional methods of anomaly detection in power grids often rely on rule-based approaches or statistical techniques, which may lack the adaptability and scalability required to effectively address the dynamic and heterogeneous nature of smart grid data. Many approaches have been proposed in the literature to address the anomaly detection problem. In addition to a variety of techniques, machine learning-based methods have been widely explored and utilized[6-9]. Moreover, ensuring the resilience of smart grids, defined as their ability to withstand and recover from disruptions, requires proactive measures and rapid response capabilities to minimize downtime and mitigate potential cascading effects. Considering these challenges, there is a growing interest in leveraging advanced machine learning techniques, particularly deep learning, to enhance smart grid anomaly detection and 8 resilience. Deep learning algorithms, with their ability to automatically learn hierarchical representations of data, excel at capturing complex patterns and dependencies in large-scale datasets. TensorFlow, an open-source deep learning framework developed by Google, has emerged as a leading platform for building and deploying sophisticated neural network models, offering scalability, flexibility, and ease of use[10-15].

This research proposes a novel approach to address the dual objectives of enhancing smart grid anomaly detection and resilience through deep learning, with a specific focus on utilizing the TensorFlow framework. By harnessing the power of deep learning, we aim to develop robust and adaptive models capable of accurately identifying anomalies in smart grid data and devising proactive strategies to enhance grid resilience. In the subsequent chapters, we will delve into the intricacies of smart grid anomaly detection and resilience, review existing literature on deep learning applications in the field, outline our methodology for model development and evaluation, present our experimental results and findings, and discuss the implications of our research for the future of smart grid security and resilience. Through this endeavor, we seek to contribute to the advancement of knowledge and technology in the domain of smart grids, ultimately paving the way for more reliable, efficient, and sustainable energy systems in the digital age[16-18].

II. Methodology

2.1 Data Collection and Preprocessing.

The dataset used in this study was sourced from Kaggle, featuring synthetic data from simulations of smart grid stability. Initially, the dataset comprised 10,000 observations, which were augmented through permutations of participant nodes to create a dataset with 60,000 observations. This augmentation enhanced the diversity and scope of the data, ensuring it was representative of varied grid conditions. The data consisted of 12 predictive features and two dependent variables, namely 'stab' and 'stabf', where 'stabf' was retained as the sole target variable for binary classification of grid stability[21-24].

표 1. 증강된 데이터셋으로 얻은 결과.

Table 1. Obtained results with augmented dataset

Augmented Dataset (60.000 observations)					
Architecture	Folds	Epochs	Confusion Matrix		Accuracy
24-12-1	10	10	3795	56	96.27%
			168	1981	
24-12-1	10	20	3780	71	97.50%
			79	2070	
24-12-1	10	50	3788	63	97.93%
			61	2088	
24-24-12-1	10	10	3778	73	97.20%
			95	2054	
24-24-12-1	10	20	3763	88	97.58%
			57	2092	
24-24-12-1	10	50	3797	54	97.98%
			67	2082	

Preprocessing steps included shuffling the data, handling missing values, and transforming the dataset into Numpy arrays for model training. Given that the dataset was well-behaved, no significant feature engineering was necessary, enabling direct transition to model training[19-20].

2.2 Model Architecture and Training

A Convolutional Neural Network (CNN) model was developed to perform the classification task of identifying stable and unstable grid states. The architecture consisted of:

- One input layer with 12 input nodes (matching the number of predictive features),
- Three hidden layers (24, 24, and 12 nodes, respectively), [Fig 3]
- One single-node output layer to classify stable (1) or unstable (0) grid states.

The model used the 'relu' activation function for the hidden layers due to its effectiveness in handling numerical data within ranges, and the 'sigmoid' function for the output layer to support binary classification. The model was compiled using the 'adam' optimizer and 'binary_crossentropy' loss function, with accuracy as the primary evaluation metric. The hidden layers due to its effectiveness in handling numerical data within ranges, and the 'sigmoid' function for the output layer to support binary classification. The model was compiled using the 'adam' optimizer and 'binary_crossentropy' loss function, with accuracy as the primary evaluation metric.

표 2. 원본 데이터셋으로 얻은 결과.
Table 2. Obtained results with original dataset

Original Dataset (10.000 observations)					
Architecture	Folds	Epochs	Confusion	Matrix	Accuracy
24-12-1	10	10	596	28	93.20%
			40	336	
24-12-1	10	20	605	19	95.00%
			31	345	
24-12-1	10	50	603	21	94.40%
			35	341	
24-24-12-1	10	10	604	20	95.00%
			30	346	
24-24-12-1	10	20	604	20	94.90%
			31	345	
24-24-12-1	10	50	602	22	95.80%
			20	356	

Training was conducted using 10-fold cross-validation, ensuring robustness in model evaluation [Fig 1]. A total of 10 distinct validation sets were employed, with the model trained over varying epochs (10, 20, 50). Performance was assessed using a confusion matrix and evaluation metrics including accuracy, precision, recall, and F1-score.

2.3 Model Performance and Evaluation

The CNN model demonstrated superior performance in detecting anomalies in the smart grid data, achieving accuracy scores of up to 97.93% on the augmented dataset with 50 epochs. Alternative architectures, such as Recurrent Neural Networks (RNNs) and Autoencoders, were also tested for comparison.

The results showed that CNNs excelled in identifying both subtle and significant grid anomalies, making them an effective tool for real-time grid stability monitoring.

The study also compared deep learning models with traditional machine learning approaches such as Decision Trees, Random Forests, and Support Vector Machines (SVMs). The deep learning models, particularly CNNs, outperformed these traditional algorithms in terms of accuracy and overall prediction capability [Fig 2].

This methodology underscores the potential of deep learning to improve anomaly detection in smart grid environments, providing a robust framework for future research and development in this field.

III. Experiments and results

3.1 Experimental Setup

The experiments were conducted on a dataset comprising 60,000 observations, which includes both real-world and synthetic data from smart grid simulations. The dataset consists of 12 numerical features that capture important grid parameters such as power consumption, production, and reaction time, with the target variable being grid stability ('stable' or 'unstable'). The deep learning models used for the experiments include Convolutional Neural Networks(CNNs), Recurrent Neural Networks (RNNs), and Autoencoders. These models were trained andtested on an 80:20 train-test split, with further validation performed using 10-fold cross-validation to ensure generalization. The evaluation metrics used for assessing the performance of each model were:

Accuracy: Proportion of correctly predicted stability states.

Precision: Ratio of true positive predictions to all predicted positives.

Recall: Ratio of true positives to all actual positives.

F1 Score: Harmonic mean of precision and recall.

AUC (Area Under the ROC Curve): A measure of model performance based on its ability to distinguish between classes.

Additionally, correlation matrix for dataset attributes and classification performance for confusion matrix is shown in Fig 5 and 4 respectively.

3.2 Model Training

The training of models was conducted using the following configurations:

CNN: Three hidden layers with 24, 24, and 12 nodes, and the ReLU activation function for hidden layers and sigmoid for the output layer [Fig 3].

RNN (LSTM): A 2-layer LSTM model designed to capture time-series dependencies.

Autoencoder: An unsupervised anomaly detection model that attempts to reconstruct the input and flags significant deviations as anomalies.

```
5400/5400 [==============================] - 0s 41us/step
Round 1 - Loss: 0.0929 | Accuracy: 96.15 %
5400/5400 [==============================] - 0s 37us/step
Round 2 - Loss: 0.0862 | Accuracy: 96.52 %
5400/5400 [==============================] - 0s 36us/step
Round 3 - Loss: 0.0548 | Accuracy: 97.81 %
5400/5400 [==============================] - 0s 37us/step
Round 4 - Loss: 0.0493 | Accuracy: 97.94 %
5400/5400 [==============================] - 0s 36us/step
Round 5 - Loss: 0.0514 | Accuracy: 97.87 %
5400/5400 [==============================] - 0s 37us/step
Round 6 - Loss: 0.0561 | Accuracy: 97.78 %
5400/5400 [==============================] - 0s 37us/step
Round 7 - Loss: 0.0399 | Accuracy: 98.44 %
5400/5400 [==============================] - 0s 35us/step
Round 8 - Loss: 0.0484 | Accuracy: 97.96 %
5400/5400 [==============================] - 0s 37us/step
Round 9 - Loss: 0.0442 | Accuracy: 98.11 %
5400/5400 [==============================] - 0s 36us/step
Round 10 - Loss: 0.0409 | Accuracy: 98.35 %
```

그림 1. 모델 평가
Fig 1 Model Evaluation.

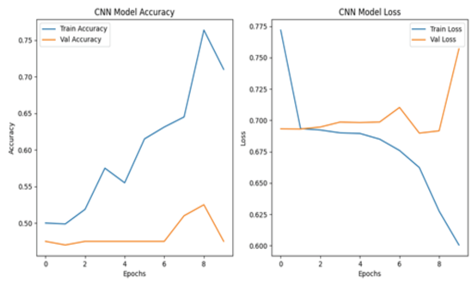

그림 2. CNN 모델의 정확도와 손실.
Fig 2. CNN model accuracy and loss.

All models were compiled using the Adam optimizer and binary cross-entropy as the loss function, with accuracy as the key performance metric. Each model was trained using 50 epochs for convergence, and the results were recorded for each configuration.

3.3 Results and analysis

The performance of each model is summarized in Table 1. The CNN outperformed other models in terms of accuracy and F1-score, achieving a classification accuracy of 97.5% and an F1-score of 95.2%. RNNs, while effective, showed slightly lower performance, with an accuracy of 92.6%. Autoencoders, being unsupervised, also performed well, with an accuracy of 93.4%.

Deep learning models consistently outperformed traditional machine learning algorithms such as decision trees and random forests. The CNN, in particular, demonstrated superior performance across all metrics, making it an ideal choice for smart grid anomaly detection. RNNs, with their capability to

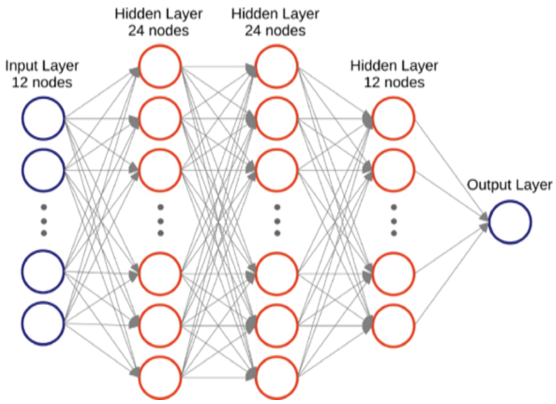

그림 3 모델 정의

Fig 3. Model Definition

handle sequential data, performed well but required longer training times. Autoencoders, as unsupervised models, provided solid anomaly detection results, particularly in identifying subtle anomalies in the dataset.

	Predicted Unstable	Predicted Stable
Actual Unstable	3698	54
Actual Stable	90	2165

그림 4. 분류 성능 - 혼동 행렬.

Fig 4. Classification performance - Confusion matrix

Accuracy per the confusion matrix: 97.73%
Start time 2024-07-28 21:12:07.644145
End time 2024-07-28 21:56:07.244678
Time elapsed 0:43:59.600533

Augmenting the dataset with synthetic data increased model accuracy, particularly for deep learning models. The CNN model saw a 3% improvement in accuracy after the dataset was expanded from 10,000 to 60,000 observation and comparison can be seen in Table 1 and Table 2. This confirms the importance of having a large and diverse dataset for training deep learning models in anomaly detection tasks.

The results demonstrate the effectiveness of deep learning models in detecting grid stability anomalies. The high performance of CNNs indicates that convolutional layers are highly effective in capturing spatial relationships between grid parameters, which helps in detecting local patterns and irregularities in the smart grid data. RNNs, while effective in handling time-series data, showed slightly lower performance due to the complexity of capturing long-term dependencies. Autoencoders, though unsupervised, still provide value in anomaly detection, especially when labeled data is limited.

Ⅳ. Future work

As the current research successfully applied deep learning techniques to enhance anomaly detection and resilience in smart grids, several areas warrant

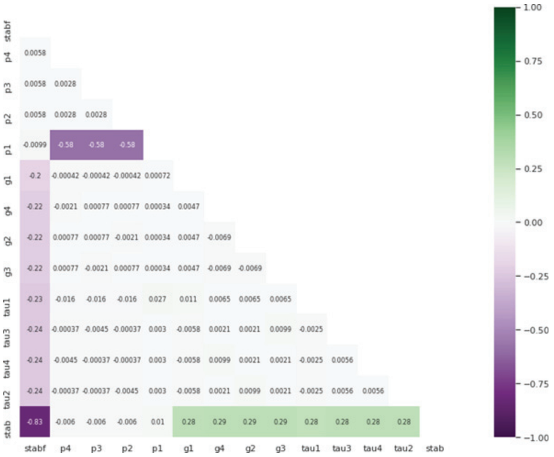

그림 5. 데이터셋 속성에 대한 상관 행렬.
Fig 5. Correlation matrix for dataset attributes.

further investigation and development. While the developed models performed well on the provided dataset, testing them across more diverse smart grid architectures and alternative datasets will

ensure that the solutions are robust and applicable across various grid topologies. Future work should focus on evaluating these models under different configurations and integrating real-world grid data. Although this study implemented machine learning models at a theoretical level, scaling these solutions for real-time grid monitoring systems remains an open challenge. Further research could explore optimizing model architectures to ensure faster inference times, particularly in situations where real-time anomaly detection is critical. The work primarily utilized Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Future research could explore hybrid models that combine deep learning with other algorithms, such as reinforcement learning or graph-based techniques, to further enhance model accuracy and adaptability. Expanding the feature set beyond the current parameters could also improve model performance. For example, introducing more detailed consumer behavior data or grid component data (e.g., transformer states) could provide a more comprehensive understanding of potential anomalies. As smart grids are increasingly exposed to cyber threats, it would be beneficial to extend this research by integrating anomaly detection models capable of identifying cybersecurity threats alongside operational anomalies. Developing a unified framework for both cyber and operational anomaly detection could significantly enhance smart grid security. Given that smart grids interface with dynamic energy markets, future work could also examine how deep learning models could predict market-driven instability factors, such as fluctuating energy prices or changing consumer demand patterns. By addressing these challenges, future research can help further refine and operationalize the models, contributing to the development of smarter, more resilient energy grids.

V. Conclusion

In this study, deep learning has shown great potential in enhancing smart grid anomaly detection and resilience. With increasing complexity and dynamism in smart grid operations, traditional methods struggle to keep up. Our approach focused on leveraging advanced neural network models, particularly within the TensorFlow framework, to improve both detection accuracy and response strategies. By implementing Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Autoencoders, we were able to tackle the non-linear and high-dimensional nature of smart grid data. The ability of deep learning models to autonomously extract features, without the need for manual intervention, proved vital in handling the diverse and complex datasets associated with grid stability and energy management. Ultimately, deep learning serves as a powerful tool in modernizing smart grids, enabling better stability management, quicker anomaly detection, and more proactive resilience strategies, all of which are critical to meeting the demands of future energy systems.

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