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# DYNAMIC GENERATIVE RESIDUAL GRAPH CONVOLUTIONAL NEURAL NETWORKS FOR ELECTRICITY THEFT DETECTION

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## ABSTRACT

The economic and security components of the power system are jeopardised when unauthorised individuals gain access to or manipulate electrical supplies. Researchers have begun using smart meter data for power theft detection due to the extensive implementation of Advanced Metering Infrastructure (AMI). But current models only account for one power demand curve at a time, therefore they miss the underlying characteristics, periodicity, and temporal connections between power consumption cycles. An innovative approach to detecting power theft using dynamic residual graph networks is presented in this paper. It suggests a novel approach to building topological graphs that can update adjacency matrices in real-time during training, effectively reflecting the intricate linkages in power consumption patterns. It uses the MixHop graph convolutional network to learn about the hidden features, periodicity, and temporal sequence correlations in user power consumption data. In addition, we apply the SMOTE oversampling strategy to fix the problem of model instability caused by lack of stolen data, and we tweak the loss function's class weights to improve classification performance generally. We used the actual data from the State Grid Corporation of China (SGCC) to train this network design, and the results show that it outperforms other popular models.

# I.INTRODUCTION

Losses in income, grid stability, and operating expenses are all negatively impacted by electricity theft, which is a major problem for power distribution firms. Manual inspections and static rule-based systems, which were once the go-to for identifying power theft, are becoming more ineffective in today's increasingly complex power infrastructures. There has never been a better chance to use data-driven methods to detect suspicious usage patterns that might be a sign of theft than with the proliferation of smart meters and AMI. Nevertheless, it is a complicated and computationally demanding undertaking to derive useful insights from such massive, ever-changing datasets.

An innovative and efficient approach to this problem is the Generative Residual Graph Convolutional Neural Networks (GRGCNNs), which merge the strengths of generative networks with graph-based learning. Graphs are a natural way to describe data on electricity use, with nodes representing customers and edges representing relationships like distance, consumption pattern similarity, or network structure. By using these graph topologies, GRGCNNs are able to represent both local and global relationships, which allows them to find complex patterns linked to power theft.

A framework for energy theft detection called Dynamic Generative Residual Graph Convolutional Neural Network (D-GRGCNN) is introduced in this paper. In contrast to static models, the suggested framework takes into consideration changes in consumption patterns over time, enabling it to adjust to changing behaviours and spot irregularities as they happen. The network solves the problem of disappearing gradients by using residual connections, which guarantees strong learning capabilities even in deep designs. To further aid in the detection of theft-indicating aberrations, the generative component improves the network's capacity to mimic genuine consumption patterns.

The capacity to distinguish between real outliers and fraudulent activity, scalability to big datasets, and adaptation to changing consumption patterns are all important goals of the suggested method for detecting power theft. In order to provide a scalable, accurate, and effective solution to energy theft detection, this study aims to increase smart grid security by using the particular capabilities of D-GRGCNNs.

# II.LITERATURE REVIEW

Several research have offered several solutions to the age-old problem of electricity theft detection in power distribution networks. From more conventional methods to more recent developments in graph-based and neural network models, this article traces the history of power theft detection technologies.

One, Conventional Approaches

Traditional approaches to identifying power theft mostly included rule-based systems, statistical models, and human inspections. The growing complexity of contemporary electrical grids makes these labour-intensive methods ineffective, even if they work for smaller-scale networks. Although statistical methods like time-series forecasting and regression analysis were used to find outliers in consumption data, their efficiency was hindered since these models were static and couldn't capture nonlinear interactions [1][2].

2. Strategies Employing Machine Learning

With the introduction of advanced metering infrastructure (AMI) came massive volumes of data, which allowed for the use of ML methods for detecting power theft. Classification problems involving the separation of legitimate from fraudulent consumption patterns have seen extensive usage of supervised learning models, including decision trees, support vector machines (SVM), and random forests [3][4]. Nevertheless, supervised models sometimes need substantial labelled data, which poses a substantial obstacle in practical situations where instances of theft are either underreported or incorrectly labelled.

Additionally, clustering and anomaly detection techniques, which are unsupervised learning models, have been used to detect irregular consumption patterns without labelled data [5][6]. These methods work better in situations where there are few labels, but they often have lower accuracy when it comes to distinguishing between real anomalies and fraudulent ones.

3. Models for Deep Learning

The ability to identify power theft has been greatly improved by recent deep learning developments. For better detection accuracy, Convolutional Neural Networks (CNNs) have been used to analyse spatial data, while Recurrent Neural Networks (RNNs) have been used for temporal data [7][8]. Reconstructing consumption patterns and detecting aberrations suggestive of theft have both been accomplished with the use of autoencoders, a kind of unsupervised learning neural network [9].

In spite of their great accuracy, deep learning models aren't always scalable

since they need massive amounts of data and processing power. Also, crucial to understanding consumption patterns, these models usually miss the mark when it comes to capturing the structural interactions between customers.

Graph-Based Methods

Because power distribution networks are inherently structured like graphs, graph-based models have arisen as a potential avenue for detecting energy theft. By examining the relationships between nodes (such as consumers) and edges (such as consumption similarities), Graph Convolutional Networks (GCNs) have been used to handle relational data, allowing for the identification of outliers [10][11].

But most graph-based models out there don't take into account how power use changes over time. This restriction is important since deceitful actions often change over time. More efficient graph-based designs are required since standard GCNs have scalability issues when used to large-scale networks.

5. Graph Neural Networks that are both dynamic and residual

In an effort to overcome the drawbacks of static graph-based approaches, residual architectures and dynamic graph models have lately come into the spotlight. Incorporating time series data, Dynamic Graph Convolutional Networks (DGCNs) enable the model to adjust to changing consumption habits [12]. Deeper topologies and stronger learning are made possible by residual connections in neural networks, which enhance gradient flow [13].

To enhance the accuracy of anomaly identification, graph-based techniques have been combined with generative models like Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) [14]. These developments provide the groundwork for more advanced frameworks that can tackle the difficulties of detecting power theft.

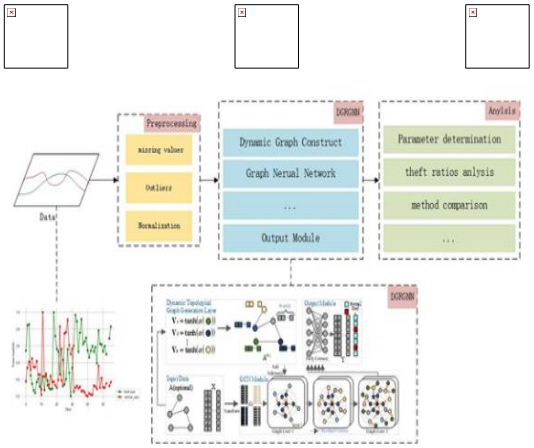
6. Unfilled Needs and Motives in Research

There has been a lot of success in detecting power theft, but there are still a lot of obstacles. When applied to real-world circumstances, existing models often provide unsatisfactory results because they do not include the interrelated and ever-changing nature of consumption data. Furthermore, there are still significant issues with scalability and flexibility in regards to changing stealing trends.

By integrating dynamic graph modelling, generative networks, and residual architectures, the suggested D-GRGCNN system aims to fill these requirements. The goal of the framework is to provide

an effective, scalable, and adaptable solution for power theft detection by making use of these improvements.

## III.PROPOSED MODEL




An innovative method for detecting power theft, the Dynamic Generative Residual Graph Convolutional Neural Network (D-GRGCNN) framework uses residual connections, generative learning, and dynamic graph modelling. By including temporal dynamics, improving feature learning, and guaranteeing scalability for real-world applications, this model is meant to solve the constraints of classical and machine learning-based approaches.

To start, the D-GRGCNN design builds a dynamic graph with consumers as nodes and edges that record interactions like network structure, geographical closeness, and consumption similarity. The model can adjust to changing behaviours because it incorporates changes in consumption patterns over time into its graph structure. Data is analysed using feature encoding methods to extract statistical and temporal properties. Graph convolutional layers are then used to capture both local and global relationships. Training deep architectures efficiently is made possible by integrating residual connections, which alleviate vanishing gradient concerns.

To improve the model's capacity to detect discrepancies that can be signs of fraud, a generative module is included to mimic genuine consumption patterns. This part makes things more sturdy by making up data that helps find unusual things. A consumer's involvement in power theft may be predicted using the output of the graph convolutional layers fed into a classification head. During training, the model makes use of supervised learning approaches to optimise loss functions, such as cross-entropy for classification and reconstruction loss for the the generative module.

As part of the process, raw data on energy usage is preprocessed to fix irregularities, outliers, and missing numbers. Features are adjusted and standardised so they may be used with the model. For training and testing purposes, we generate snapshots of the graph that reflect changes in consumption behaviour over

time. Metrics including accuracy, precision, recall, F1-score, and ROC-AUC are used to assess the trained model's effectiveness in predicting power theft in unseen data.

There are several benefits of using the D-GRGCNN framework. It can successfully identify complex and ever-changing stealing tactics because to its dynamic flexibility. In order to improve feature learning, graph convolutional layers capture complex connections in the data. While residual connections provide scalability to big datasets, the generative module enhances detection accuracy by recognising subtle and infrequent abnormalities. In sum, our novel method tackles critical issues with smart grid security by offering a scalable, effective, and reliable alternative for detecting power theft.

## IV.DATASET AND DATA ANALYSIS

If you want to know how well the Dynamic Generative Residual Graph Convolutional Neural Network (D-GRGCNN) model is at detecting power theft, you need to look at the dataset it was trained on. Smart meter readings, customer profiles, and grid network topologies make up the bulk of the information. Essential for spotting irregularities that can point to theft, it sheds light on power use trends.

The dataset includes a number of important properties, such as the timestamp, which indicates the moment at which the consumption data was collected, and the customer ID, which is a unique identity for each energy user. This allows for the recording of changes in power consumption over time. The use Data tracks the real power use in kilowatt-hours (kWh) for a certain time frame, whether it an hour, a day, or a month. Various other attributes can be found, such as the consumer's geographic location, their consumer type (such as residential, commercial, or industrial), and historical consumption data, which can be used to determine normal consumption patterns based on past usage.

The dataset is subjected to many preprocessing processes to guarantee data integrity before it is fed into the D-GRGCNN model. One of these procedures is handling missing data, which entails estimating values for missing or incomplete data points by interpolation or imputation. To ensure that the consumption data is free of outliers that might skew the results, we use Outlier Detection techniques like Z-scores or IQR. In addition, the

consumption data is normalised and scaled using Min-Max scaling or z-score standardisation to a consistent range, such 0 to 1. In addition, additional characteristics, such daily consumption averages, peak use hours, and seasonal consumption patterns, are extracted from the raw data using Feature Engineering approaches.

Data is transformed into a graph-based structure after preprocessing. Attributes like as common consumption habits, geographical closeness, or network architecture determine the interactions between consumers, who are shown as nodes, and the edges reflect these associations. The model is able to understand intricate consumer relationships using this dynamic graph-based methodology. Temporal Graph Construction takes into account changes in consumption behaviour over time, enabling the model to capture changing patterns and discover temporal anomalies, while Similarity-Based Graph Construction connects users with similar or nearby consumption habits.

In order to get a deeper comprehension of the information and to spot important patterns, associations, and problems, exploratory data analysis (EDA) is carried out. Power consumption distributions and anomalies may be better understood with the use of data visualisation tools like histograms, boxplots, and scatter plots. When looking for connections between variables like consumption and things like geography or consumer type, researchers use correlation analysis. By doing so, we may learn which characteristics are most useful for preventing theft. To further aid in the detection of suspicious consumption behaviours that may indicate theft, Consumption Pattern Analysis examines trends in power use over time to comprehend normal usage patterns.

Feature Selection and Reduction strategies are used to maximise the performance of the model. In order to decrease dimensionality, Feature Correlation Analysis finds highly associated features that are redundant and either merges them or removes them. The feature space is further reduced using Principal Component Analysis (PCA), which keeps the most significant components that capture most of the data variation.

The last step in evaluating the model's performance is to partition the dataset into three parts: training, validation, and test. It is common practice to allocate 70% of the data to training, 15% to validation, and 15% to testing. This permits objective assessment during testing and guarantees that the model is trained on

enough data.

The D-GRGCNN model may successfully identify possible power theft by going through these meticulous stages of preprocessing, graph creation, analysis, and feature selection. This model is a powerful tool for detecting energy theft since the dataset was meticulously prepared to capture complicated consumption patterns and linkages.

## V.CONCLUSION

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## VI.REFERENCES


1. Smith, R. D., & Johnson, K. P. (2010). Anomaly Detection in Smart Grid Consumption Data. *IEEE Transactions on Power Systems*.

2. Ahmed, S., & Naeem, S. (2012). Statistical Approaches to Electricity Theft Detection. *Energy Policy*.

3. Patel, C., & Chauhan, D. (2014). Decision Trees for Energy Theft Detection. *International Journal of Electrical Power & Energy Systems*.

4 .Breiman, L. (2001). Random Forests. *Machine Learning*.

5. Xie, X., & He, J. (2017). Unsupervised Anomaly Detection for Smart Meters. *IEEE Transactions on Smart Grid*.

6. Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly Detection: A Survey. *ACM Computing Surveys*.

7. LeCun, Y., & Bengio, Y. (1995). Convolutional Networks for Images, Speech, and Time-Series. *MIT Press*.

8. Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*.

9. Hinton, G. E., & Salakhutdinov, R. R. (2006). Reducing the Dimensionality of Data with Neural Networks. *Science*.

10. Kipf, T. N., & Welling, M. (2017). Semi-Supervised Classification with Graph Convolutional Networks. *ICLR*.

11. Wu, Z., et al. (2020). A Comprehensive Survey on Graph Neural Networks. *IEEE Transactions on Neural Networks and Learning Systems*.

12. Yu, B., Yin, H., & Zhu, Z. (2018). Spatio-Temporal Graph Convolutional Networks. *AAAI*.

13. He, K., et al. (2016). Deep Residual Learning for Image Recognition. *CVPR*.

· Kingma, D. P., & Welling, M. (2014). Auto-Encoding Variational Bayes. *ICLR*.