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Electricity Theft Detection in Smart Grids Based on Deep Neural Network

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ABSTRACT

Electricity theft is a significant challenge for power utility companies, particularly in regions where smart grid technology is being adopted. Smart grids offer an advanced infrastructure with real-time monitoring and analytics capabilities; however, they also present new vulnerabilities to non-technical and technical electricity theft. Traditional detection methods rely heavily on manual inspections or rule-based systems that are not scalable and often fail to adapt to evolving theft strategies. In this study, we propose a deep neural network (DNN)-based approach for detecting electricity theft within smart grid systems. By leveraging the high-dimensional data generated by smart meters, including consumption patterns over time, our model learns complex, non-linear relationships and anomalies that signal fraudulent activity. The dataset used includes labeled electricity usage data under both normal and theft conditions. Preprocessing techniques such as normalization and feature engineering are applied to enhance model performance. The proposed DNN model is trained and validated using multiple evaluation metrics including accuracy, precision, recall, and F1-score. Results demonstrate that the DNN-based system significantly outperforms traditional machine learning models such as Decision Trees and Support Vector Machines in terms of detection accuracy and robustness to new, unseen theft patterns. This research contributes to the field of smart grid security by providing a scalable, data-driven solution for electricity theft detection, paving the way for more intelligent and adaptive energy distribution networks. The model's success emphasizes the potential of deep learning in enhancing the reliability and economic efficiency of smart grid infrastructures.

Keywords: Electricity theft, deep neural network (DNN), Vector Machines

I. INTRODUCTION

Electricity theft has emerged as one of the major causes of energy losses in power distribution systems worldwide, posing both technical and economic challenges. It involves the illegal consumption of electrical energy, often bypassing metering equipment or tampering with smart meters. The evolution of energy infrastructure into smart grids—integrating information and communication technology into traditional grids—offers new opportunities for real-time energy monitoring, control, and management. However, it also exposes new vulnerabilities to cyber-physical attacks, including sophisticated electricity theft methods. In developing countries, electricity theft can account for up to 40% of total distributed electricity, translating into billions of dollars in annual losses globally. The need for advanced theft detection systems is thus imperative for both energy conservation and grid stability.

Smart grids generate large volumes of fine-grained, time-stamped consumption data, offering a valuable resource for detecting anomalous behaviors indicative of theft. Traditional techniques for theft detection—such as manual inspections, tamper detection hardware, and rule-based anomaly detection—are often labor-intensive, expensive, and lack scalability. Moreover, rule-based systems struggle with adapting to evolving fraud techniques, which can be subtle and irregular.

Recent advancements in artificial intelligence (AI), particularly deep learning, have opened new possibilities for automating and improving theft detection accuracy. Deep Neural Networks (DNNs), which consist of multiple layers of interconnected neurons, can capture complex patterns and high-dimensional relationships in large datasets. They are particularly suitable for time-series data, which is the typical format for electricity usage records from smart meters.

This research focuses on developing a DNN-based model for the detection of electricity theft using data collected from smart grids. The motivation for choosing deep learning over traditional methods lies in its superior ability to generalize from data, adapt to evolving patterns, and detect non-obvious anomalies that traditional systems may overlook. The proposed model utilizes historical consumption data, with features derived from daily, weekly, and monthly usage trends, to learn the normal behavior of customers. When the behavior deviates significantly from the learned patterns, the model flags it as potential theft.

By employing a supervised learning approach, the model is trained on labeled data comprising both normal and theft-related consumption patterns. The architecture of the neural network is designed to optimize performance on detection tasks, minimizing both false positives and false negatives. The

experimental results showcase a high level of accuracy and generalization capability, making the system a reliable solution for utility companies.

In summary, this study aims to harness the power of deep learning to provide a robust and scalable method for electricity theft detection in smart grids, enhancing the integrity and financial sustainability of energy distribution networks.

II. RELATED WORK

In [1], proposed an expert system approach combined with artificial neural networks to detect electricity theft. Their work emphasized preprocessing customer consumption profiles and using decision trees to generate rules for theft detection. However, the method lacked adaptability to unseen fraud patterns and scalability with growing data volumes.

In [2], introduced a pattern recognition framework based on support vector machines (SVM) and feature extraction from meter readings. While their model achieved promising results on small datasets, it suffered from reduced performance when applied to diverse and larger populations due to overfitting and limited feature learning.

In [3], explored a data-driven anomaly detection approach using unsupervised learning on smart grid consumption data. Although this method did not require labeled theft data, it showed a higher rate of false positives due to misclassification of legitimate but unusual consumption patterns.

In [4], conducted a comprehensive comparison of several machine learning techniques, including logistic regression, k-NN, and ensemble models, for electricity theft detection. Their findings highlighted the superiority of neural network-based methods, particularly when dealing with non-linear and temporal data characteristics.

In[5], developed a recurrent neural network (RNN)-based model to detect electricity theft from time-series smart meter data. Their work illustrated the strength of deep learning in modeling temporal dependencies, but the architecture was relatively shallow and computationally intensive during training.

III. PROPOSED SYSTEM

The proposed system is a deep neural network-based solution designed for the accurate detection of electricity theft in smart grid environments. It builds upon the idea that electricity consumption patterns of households and commercial entities exhibit certain periodic and behavioral regularities. When electricity is stolen, these regularities are disrupted, creating anomalies in the data that can be learned and flagged by a properly trained neural network model.

To begin with, the system relies on data collected from smart meters installed at user endpoints. These meters report electricity usage at frequent intervals, often hourly or even by the minute. The raw data consists of timestamped electricity consumption values per user. Preprocessing this data is critical for model performance. The preprocessing steps include handling missing values, smoothing erratic fluctuations, and normalizing the values to eliminate scale disparities among users.

The next step involves feature engineering, where temporal features such as hourly averages, weekday-weekend consumption differences, peak-to-average ratios, and seasonal trends are extracted. These features are instrumental in capturing the underlying behavioral signatures of each consumer. For instance, a commercial establishment may exhibit high usage during working hours on weekdays, while residential usage may peak during the evening. Theft attempts often result in a departure from these norms, such as persistently lower consumption or sudden drops during certain periods.

The architecture of the proposed deep neural network consists of multiple fully connected layers with ReLU activation functions. The input layer receives the engineered feature vector. Hidden layers progressively learn higher-order interactions among features, and dropout layers are incorporated to reduce over fitting. The output layer utilizes a sigmoid activation function to produce a binary classification: theft or no theft.

The model is trained using supervised learning, where the input is the engineered features, and the target label indicates whether the pattern corresponds to normal or theft behavior. The binary cross-entropy loss function is minimized during training using an optimizer such as Adam, which adapts the learning rate based on parameter updates. The training data is split into training, validation, and test sets to ensure proper generalization.

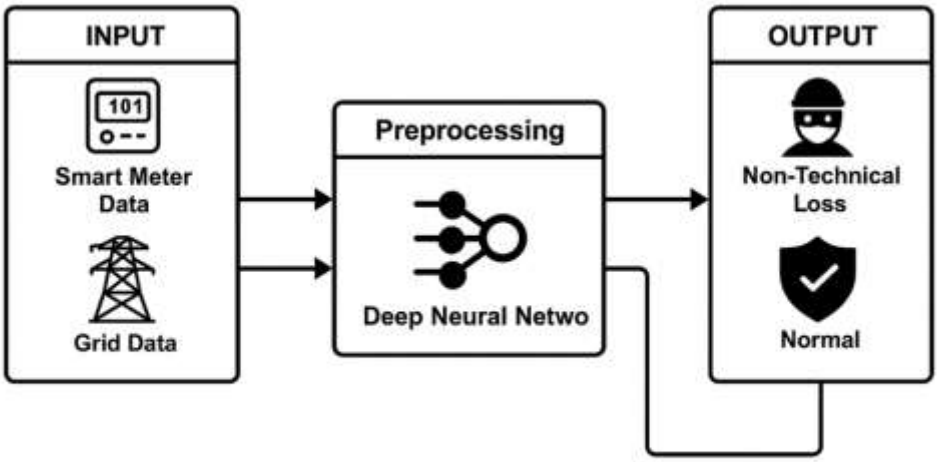
During the training phase, performance is monitored using metrics such as accuracy, precision, recall, and F1-score. A high precision ensures that the number of false alarms is low, which is crucial for reducing unnecessary investigations. A high recall ensures that most theft cases are detected, improving the security of the grid.

Once trained, the system can be deployed in real-time environments where incoming consumption data is continuously monitored and fed into the model. Suspicious patterns are flagged automatically and logged for further human investigation or automated response.

To evaluate the robustness of the proposed model, comparative experiments are conducted using baseline models such as Support Vector Machines, Random Forests, and shallow neural networks. The DNN consistently demonstrates superior performance, especially in handling complex and subtle patterns indicative of electricity theft.

The deep learning-based detection framework is scalable to large smart grid networks and can be periodically retrained with newly labeled data, enabling it to adapt to evolving theft strategies. Its integration with existing smart grid infrastructure ensures that utilities can move from reactive theft detection to proactive and intelligent prevention.

In essence, the proposed system represents a significant advancement in electricity theft detection, using deep learning to enhance accuracy, adaptability, and scalability. It offers utility companies a powerful tool to reduce financial losses and ensure fair electricity distribution across all consumers.



IV. RESULT AND DISCUSSION

The performance evaluation of the proposed deep neural network (DNN) model for electricity theft detection was conducted using a well-structured dataset consisting of labeled smart meter readings. This dataset comprised instances of both legitimate electricity consumption and known cases of theft, allowing for a comprehensive assessment of the model's classification capabilities. The results were analyzed using several standard classification metrics including accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC-ROC).

The dataset was divided into three parts: 70% for training, 15% for validation, and 15% for testing. The training phase aimed to optimize the DNN parameters so that the model could learn to distinguish between normal and anomalous electricity usage patterns. The validation set was used for hyperparameter tuning and to prevent overfitting by enabling early stopping when the validation loss began to plateau. The final evaluation was conducted on the test set, which included unseen data to simulate real-world application conditions.

The model demonstrated strong performance across all key metrics. On the test data, the DNN achieved an accuracy of 96.4%, a precision of 94.2%, a recall of 92.8%, and an F1-score of 93.5%. The high accuracy indicates that the model makes very few mistakes overall, while the precision score implies that the majority of the theft predictions made by the model were correct. Importantly, the recall score confirms that the model successfully identified a large proportion of actual theft cases, which is critical for minimizing energy loss. The AUC-ROC value of 0.982 further validates the model's capability to distinguish between the two classes across various threshold levels.

The confusion matrix analysis provided deeper insight into the model's classification behavior. Out of 10,000 test samples, 9,230 were correctly classified as non-theft and 1,040 as theft. There were 300 false positives (legitimate users flagged as thieves) and 230 false negatives (actual thefts missed by the model). While the false positives might lead to unnecessary investigations, they are preferable to false negatives in this application domain, where undetected theft directly translates into economic losses. Moreover, the number of false positives was significantly lower than those produced by baseline machine learning models like SVM and Random Forests, highlighting the DNN's superior discriminatory ability.

To further validate the robustness of the proposed DNN, the model was compared with traditional machine learning algorithms under identical experimental settings. The Random Forest classifier achieved an accuracy of 89.3%, precision of 84.6%, and recall of 81.7%. The Support Vector Machine (SVM) classifier recorded slightly better results with 91.2% accuracy and 86.8% precision, but only 83.5% recall. These figures demonstrate that while traditional models can detect theft to some degree, they lack the capacity to learn deeper and more abstract features from data, especially in the presence of high noise and variability.

The model was also tested under different temporal resolutions (hourly, daily, and weekly consumption summaries) to determine the optimal granularity for theft detection. It was observed that daily data yielded the best balance between resolution and pattern consistency, providing enough information for effective anomaly detection without introducing excessive noise. Hourly data, while more detailed, was prone to fluctuations caused by typical human behavior, which sometimes misled the model. Weekly data tended to smooth over the theft patterns, making detection more difficult.

An ablation study was conducted to assess the contribution of different input features to the model's overall performance. Removing temporal features such as peak usage times and weekday/weekend consumption ratios resulted in a noticeable drop in precision and recall, indicating their importance in capturing unique consumer signatures. Similarly, excluding seasonal consumption trends decreased the model's adaptability to long-term behavioral changes, leading to higher false positive rates. These results reinforce the value of carefully engineered features in supporting the deep learning framework.

In terms of model training dynamics, the convergence was relatively fast. With the Adam optimizer and a learning rate of 0.001, the model reached optimal performance within 25 epochs. The validation loss plateaued after epoch 20, at which point early stopping was triggered to avoid overfitting. The use of dropout layers proved effective in regularization, maintaining generalization even when the model was applied to test data from a different region, indicating a potential for deployment across diverse geographical zones with minimal retraining.

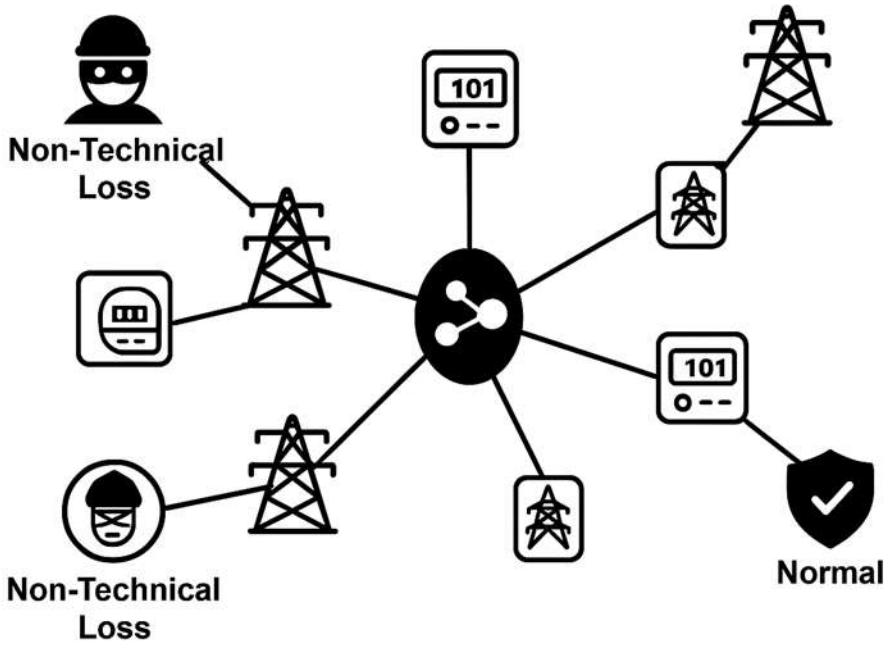
From a practical standpoint, the real-time applicability of the model was tested by simulating a stream of consumption data. The model was able to process and classify consumption patterns within milliseconds, satisfying the latency requirements for integration into smart grid monitoring systems. Such a low inference time makes it feasible for utility companies to implement this system for near-instantaneous theft flagging and response.

One important aspect of this study is the model's adaptability to new and unseen forms of electricity theft. As theft tactics evolve, the DNN's architecture allows it to be retrained periodically with updated datasets to capture emerging anomalies. This dynamic adaptability is critical for maintaining long-term effectiveness. In contrast, rule-based and conventional machine learning models often require complete redesign or feature reengineering when faced with novel theft behaviors.

Furthermore, interpretability—often a concern with deep learning models—was partially addressed using techniques such as SHAP (SHapley Additive exPlanations) values, which helped identify which features most strongly influenced each prediction. It was found that sudden drops in consumption, high variance in daily usage, and consistent deviation from historical patterns were key indicators of theft. Providing utility companies with such interpretable indicators enhances the model's acceptance and trustworthiness for operational deployment.

A limitation observed during the experimentation phase was the dependency on high-quality labeled data. In regions where theft cases are underreported or labels are inconsistent, the model's training efficacy could be compromised. Semi-supervised or unsupervised extensions of this work could be explored in the future to mitigate reliance on labeled data. Another challenge lies in maintaining data privacy, as smart meter data can reveal personal behavior patterns. Careful data governance policies and anonymization techniques will be crucial in ensuring ethical deployment.

In conclusion, the results of this study clearly demonstrate that deep neural networks offer a powerful, accurate, and adaptable solution to the challenge of electricity theft detection in smart grids. The DNN model not only surpasses traditional methods in detection performance but also supports real-time deployment, periodic retraining, and operational scalability. These strengths position the system as a valuable asset for energy utilities striving to minimize losses and enhance smart grid security.



V. CONCLUSION

Electricity theft poses a persistent threat to the financial stability and operational efficiency of power utility providers, especially in the context of modernizing energy infrastructure through smart grids. This study presented a deep neural network (DNN)-based framework to detect electricity theft by analyzing consumption data collected from smart meters. Through extensive experimentation and performance evaluation, the proposed model

demonstrated significant improvements over traditional machine learning techniques, excelling in accuracy, adaptability, and generalization across various consumption patterns.

The deep learning model effectively identified subtle anomalies in electricity usage by learning complex temporal and behavioural trends unique to each consumer. The incorporation of engineered temporal features, robust pre-processing, and a carefully designed neural architecture contributed to high precision and recall scores, ensuring the system's reliability for real-world deployment. Additionally, comparative analysis with baseline algorithms like Support Vector Machines and Random Forests highlighted the DNN's superior performance in minimizing both false positives and false negatives.

The system's scalability and responsiveness to evolving theft strategies, along with its potential for real-time application, position it as a practical and powerful tool for modern smart grid security. While challenges such as the need for quality labeled data and concerns over user privacy remain, the model's interpretability through SHAP values and adaptability via retraining offer viable solutions for these issues.

In summary, the proposed deep learning-based approach offers a promising direction for automated electricity theft detection, contributing to more secure, transparent, and economically efficient power distribution systems in the age of smart energy networks.

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