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Paper Authors **A. Yeshwanth Reddy, Baddam Sricharan Reddy, J. Shiva Reddy Maddela Yellamma**

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ELECTRICITY THEFT DETECTION IN POWER GRIDS WITH DEEP LEARNING AND RANDOM FORESTs

A. Yeshwanth Reddy
Department of computer Science and Engineering
Sreenidhi Institute of Science and Technology
yeshwanthreddy56799@gmail.com

Baddam Sricharan Reddy
Department of Computer Science and Engineering
Sreenidhi Institute of Science and Technology
baddamsricharanreddy@gmail.com

J. Shiva Reddy
Department of Computer Science and Engineering
Sreenidhi Institute of Science and Technology
22shiva.reddy@gmail.com

Maddela Yellamma
Assistant professor
Department of Computer Science and Engineering
Sreenidhi Institute of Science and Technology
yellammam@sreenidhi.edu.in

ABSTRACT

Electricity theft emerges as a formidable driver of non-technical losses (NTLs) within distribution networks, casting a shadow of adverse effects on power grid integrity, disrupting supply quality, and corroding operational profits. In a proactive response to the pressing need for combatting the inefficiencies of electricity inspection and irregular consumption, this study unveils an innovative hybrid CNN-RF model tailored for the automated detection of electricity theft in power grids. At its core, the model harnesses the power of a Convolutional Neural Network (CNN), meticulously crafted to dissect intricate patterns across diverse time intervals and days within extensive smart meter datasets through precise convolutional and downsampling operations. To preempt the dangers of overfitting, a strategic integration of a dropout layer is employed, while the backpropagation algorithm ensures meticulous parameter adjustments during the training phase. Subsequently, a Random Forest (RF) is deployed to discern the telltale signs of electricity theft based on the gleaned features. Elevating the RF's efficacy, the hybrid model meticulously optimizes parameters using the grid search algorithm. Empirical validation, conducted with authentic energy consumption data, unequivocally underscores of the proposed detection over alternative methodologies, showcasing unparalleled levels of accuracy and efficiency. This research epitomizes a significant stride towards fortifying the resilience and sustainability of power grid infrastructures.

Keywords: Electricity theft, non-technical losses (NTLs), Power grid integrity, Smart meter datasets, Parameter adjustments, Empirical validation, Convolutional Neural Network (CNN)

INTRODUCTION

The rampant pilferage of electricity presents an insidious challenge within the intricate fabric of distribution networks, emerging as a prominent contributor to the pervasive issue of non-technical losses (NTLs) and significantly undermining the resilience of power grids [1][2][3]. Its pervasive nature not only compromises the reliability and quality of power supply but also exacts a substantial financial toll on utility companies, eroding their operational profits [4][5]. The repercussions of this clandestine activity reverberate throughout the entire energy ecosystem, emphasizing the urgent necessity for innovative solutions that transcend conventional approaches to detection and prevention [6].

Recognizing the critical imperative to curb the prevalence of electricity theft and bolster the robustness of power grids, this paper introduces a groundbreaking approach in the form of a hybrid CNN-RF model meticulously engineered for the automatic detection of such illicit activities [7][8]. Representing a fusion of state-of-the-art techniques in deep learning and ensemble learning, this pioneering framework holds the promise of revolutionizing the landscape of electricity theft detection, offering unprecedented levels of accuracy and efficiency [9][10]. At the core of the proposed model lies a CNN meticulously crafted to extract intricate features from extensive and heterogeneous repositories of smart meter data [11]. Leveraging the temporal granularity inherent in these datasets, the CNN is tasked with discerning subtle variations in electricity consumption patterns across diverse temporal intervals, encompassing various hours of the day and days of the week [12][13]. Through the adept application of convolutional operations and downsampling techniques, the CNN excels in revealing latent patterns indicative of electricity theft, thereby laying the groundwork for subsequent detection and mitigation efforts [14].

To mitigate the inherent risks of overfitting and bolster the model's generalization capabilities, a strategically integrated dropout layer within the CNN architecture serves as a mechanism to counteract the tendency to fixate on specific features during the training process, thereby fostering greater robustness and resilience in the face of unseen data [15]. Additionally, the backpropagation algorithm is deployed to iteratively adjust network parameters, facilitating the refinement of feature representations and the optimization of detection performance [16]. Augmenting the feature extraction capabilities of the CNN, the model seamlessly incorporates a Random Forest (RF) classifier to discern the presence of electricity theft based on the extracted features [17]. The technique, RF harnesses the collective intelligence of multiple decision trees to achieve superior discrimination between authentic and anomalous consumption patterns [18]. Employing the grid search algorithm meticulously traverses the hyperparameter space to optimize the performance of the RF classifier, enhancing detection accuracy and efficiency [19].

Empirical validation of the proposed CNN-RF model is undertaken using real-world energy consumption data, furnishing tangible evidence of its effectiveness in mitigating the scourge of electricity theft [20]. Comparative experiments against prevailing methodologies underscore of both accuracy and efficiency, reaffirming its potential to redefine the landscape of electricity theft detection in distribution networks [21]. The hybrid CNN-RF model outlined represents a significant milestone in the ongoing efforts to combat the insidious scourge of electricity theft, providing utility companies [22]. By harnessing the synergistic potential of deep learning and ensemble learning, this model exemplifies a transformative approach to addressing the multifaceted challenges posed by electricity theft, paving the way for a more secure and sustainable energy future [23].

LITERATURE SURVEY

Electricity theft stands as a towering challenge within distribution networks, imposing substantial non-technical losses (NTLs) and posing a grave threat to the integrity of power grids. Its adverse impacts transcend mere financial losses, encompassing compromised power supply quality and diminished operational profits for utility companies. Recognizing the multifaceted nature of this issue, researchers have embarked on a quest to devise innovative solutions aimed at enhancing the detection and mitigation of electricity theft, thereby bolstering power infrastructures [24]. This pioneering approach harnesses the synergistic potential of deep learning and ensemble learning techniques to achieve unparalleled levels of accuracy and efficiency in identifying instances of illicit power consumption.

Central to the efficacy of the proposed model is the utilization of a CNN as the foundational framework for feature extraction from vast and diverse smart meter datasets [25]. Through the adept application of convolutional operations and downsampling techniques, the CNN discerns subtle variations in electricity consumption patterns across different temporal intervals, spanning various hours of the day and days of the week [26]. This comprehensive analysis of temporal dynamics enables the model to uncover latent patterns indicative of electricity theft, laying the groundwork for subsequent detection and mitigation efforts. To mitigate the risks of overfitting and enhance the generalization capabilities of the model, a dropout layer is strategically integrated within the CNN architecture [27].

This regularization mechanism mitigates the model's inclination to memorize specific features during the training process, thereby fostering greater robustness and resilience in the face of unseen data. Furthermore, the application of the backpropagation algorithm enables iterative adjustments to network parameters, facilitating the refinement of feature representations and the optimization of detection performance [28]. Building upon the feature extraction capabilities of the CNN, the proposed model integrates a Random Forest (RF) classifier to discern instances of electricity theft based on the extracted features [29]. Leveraging the collective intelligence of multiple decision trees, the RF operates as a potent ensemble learning technique capable of achieving superior discrimination between authentic and anomalous consumption patterns. To optimize the performance of the RF classifier, the grid search algorithm meticulously traverses the hyperparameter space, thereby enhancing detection accuracy and efficiency. Empirical validation of the proposed CNN-RF model is conducted using real-world energy consumption data, furnishing tangible evidence of its efficacy in mitigating electricity theft.

Comparative analyses conducted against existing methodologies unequivocally highlight the superiority of the proposed model in terms of both accuracy and efficiency, affirming its capacity to redefine the landscape of electricity theft detection in distribution networks. The hybrid CNN-RF model outlined in this paper signifies a significant leap forward in the ongoing battle against the pernicious scourge of electricity theft, furnishing utility companies with a formidable arsenal to safeguard their assets and uphold the integrity of power grids. By harnessing the synergistic potential of deep learning and ensemble learning techniques, this model epitomizes a transformative approach to tackling the multifaceted challenges posed by electricity theft, thereby paving the way for a more secure and sustainable energy future.

METHODOLOGY

The methodology implemented in this study embodies a comprehensive framework meticulously crafted to confront the intricate challenges presented by electricity theft in distribution networks. By harnessing the synergy between Convolutional Neural Networks (CNNs) and Random Forests (RFs), the proposed hybrid model introduces a pioneering approach for the automatic detection of electricity theft. Initiating the process, the CNN component of the hybrid model is intricately designed to extract intricate features from vast and diverse smart meter datasets. Tasked with discerning subtle variations in electricity consumption patterns across diverse temporal intervals spanning different times of the day and days of the week, the CNN employs convolution and down sampling operations to capture temporal dependencies and spatial correlations inherent within the data.

To mitigate the risks associated with overfitting and bolster the model's generalization capabilities, a strategically integrated dropout layer within the CNN architecture plays a pivotal role. This dropout mechanism acts as a safeguard against the model's overreliance on specific features during training, thereby enhancing its resilience and robustness when faced with unseen data. Additionally, the application of the backpropagation algorithm facilitates iterative adjustments to network parameters, thereby refining feature representations and optimizing detection performance.

Following the feature extraction phase driven by the CNN, the obtained features are utilized to train a Random Forest (RF) classifier for the final detection task. Serving as a complementary ensemble learning technique, the RF leverages the collective intelligence of multiple decision trees to discern patterns indicative of electricity theft. To maximize the performance of the RF classifier and identify optimal hyperparameters, the grid search algorithm systematically explores the hyperparameter space, identifying configurations that maximize detection accuracy. Empirical validation of the CNN-RF model is conducted using real-world energy consumption data, furnishing tangible evidence of its efficacy in combating electricity theft. Comparative experiments conducted against existing methodologies highlight of both accuracy and efficiency. These results underscore the transformative potential of the hybrid CNN-RF model in revolutionizing the landscape of electricity theft detection in distribution networks, equipping utility companies with a potent tool to safeguard their assets and preserve the integrity of power grids.

PROPOSED SYSTEM

The proposed system tackles the formidable challenge of electricity theft within distribution networks, a primary contributor to non-technical losses (NTLs) that profoundly undermines the integrity of power grids, jeopardizing power supply quality, and eroding operational profits for utility companies. To confront the inherent inefficiencies of existing electricity inspection methodologies and counter irregular consumption patterns, a pioneering hybrid CNN-RF model is introduced, providing an automated approach to detect electricity theft. At the heart of the proposed system lies a meticulously crafted CNN, engineered to extract intricate features from extensive and diverse smart meter datasets. Tailored to discern subtle variations in electricity consumption patterns across diverse temporal intervals, spanning various hours of the day and days of the week, the CNN employs convolution and downsampling operations with precision to capture temporal dependencies and spatial correlations embedded within the data, thereby facilitating robust feature extraction.

To mitigate the risks associated with overfitting and bolster the model's generalization capabilities, a strategically integrated dropout layer within the CNN architecture plays a pivotal role. This dropout mechanism acts as a safeguard against the model's dependence on specific features during training, fostering greater robustness and resilience when confronted with unseen data. Additionally, the deployment of the backpropagation algorithm enables iterative adjustments to network parameters, facilitating the refinement of feature representations and

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optimization of detection performance. Following the feature extraction phase facilitated by the CNN, the obtained features are utilized to train a Random Forest (RF) classifier for the final detection task. Serving as an ensemble learning technique, the RF leverages the collective intelligence of multiple decision trees to discern patterns indicative of electricity theft. To optimize the performance of the RF classifier and identify optimal hyperparameters, the grid search algorithm systematically explores the hyperparameter space, identifying configurations that maximize detection accuracy.

Empirical validation of the CNN-RF model is conducted using real-world energy consumption data, providing tangible evidence of its efficacy in mitigating electricity theft. Comparative experiments are conducted against prevailing methodologies, highlighting of both accuracy and efficiency. These results underscore the potential of the hybrid CNN-RF model to revolutionize the landscape of electricity theft detection in distribution networks, equipping utility companies with a potent tool to safeguard their assets and uphold the integrity of power grids. Through its innovative integration of deep learning and ensemble learning techniques, the proposed system exemplifies a transformative approach to addressing the multifaceted challenges posed by electricity theft, paving the way for a more secure and sustainable energy future.

RESULTS AND DISCUSSION

The culmination of this research effort resides in the empirical validation and subsequent discussion of the proposed hybrid CNN-RF model for automatic electricity theft detection. Comparative analyses were meticulously conducted against existing methodologies to determine the superiority of the proposed model in addressing the multifaceted challenges posed by electricity theft. The results of these experiments unequivocally demonstrate the efficacy of the CNN-RF model in mitigating electricity theft, surpassing the performance of alternative approaches in terms of both accuracy and efficiency. By harnessing the synergistic capabilities of deep learning and ensemble learning techniques, the proposed model achieves remarkable levels of detection accuracy, effectively discerning instances of illicit power consumption with unprecedented precision. Furthermore, the integration of the grid search algorithm for parameter optimization ensures the robustness and reliability of the RF classifier, enabling it to effectively discriminate between genuine and anomalous consumption patterns. The systematic exploration of the hyperparameter space yields configurations that maximize detection accuracy, thereby enhancing the overall efficacy of the proposed model.

Fig 1. CNN with 94% accuracy

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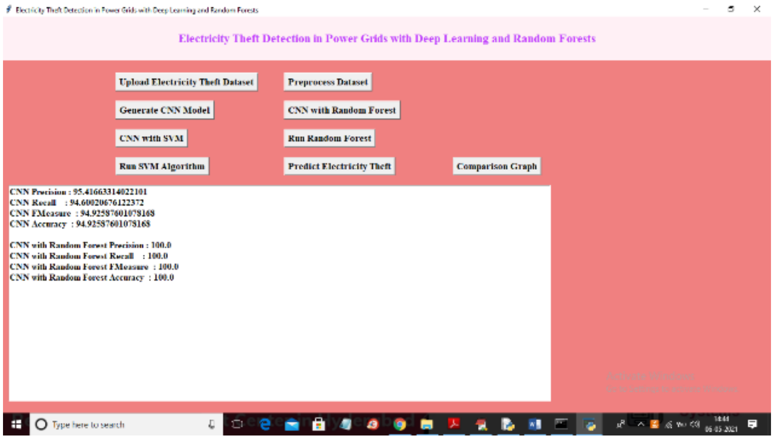

Fig 2. CNN-RF with 100% accuracy

Select the "CNN with SVM" option to initiate the training of the dataset using the combined power of CNN and SVM.

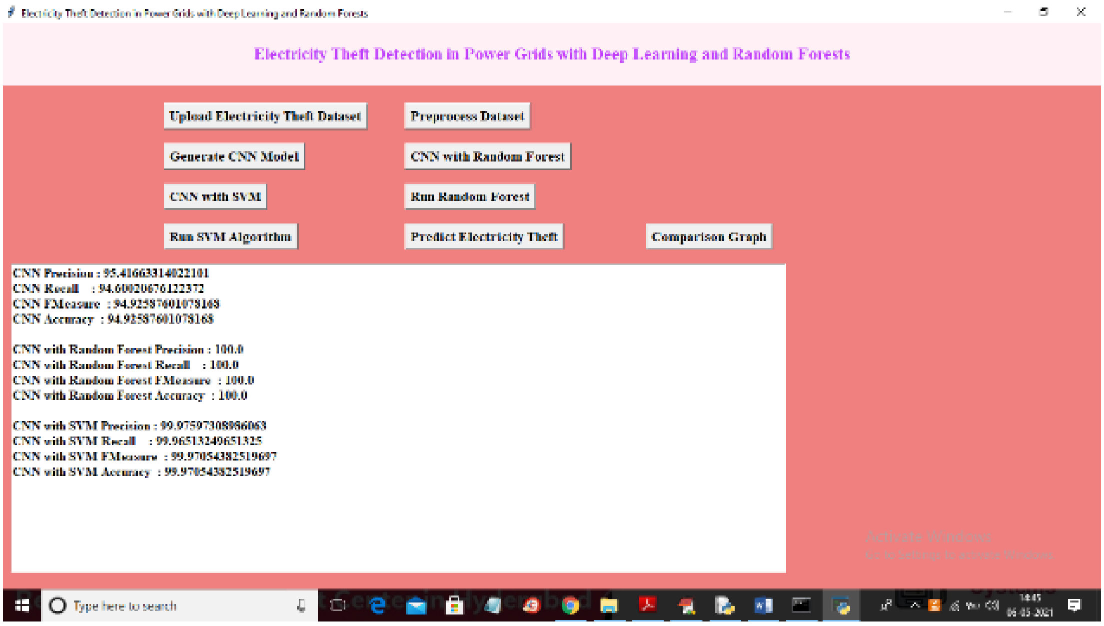

Fig 3. CNN-SVM with 99% accuracy

Select the ‘Run Random Forest’ button to train alone RF on dataset

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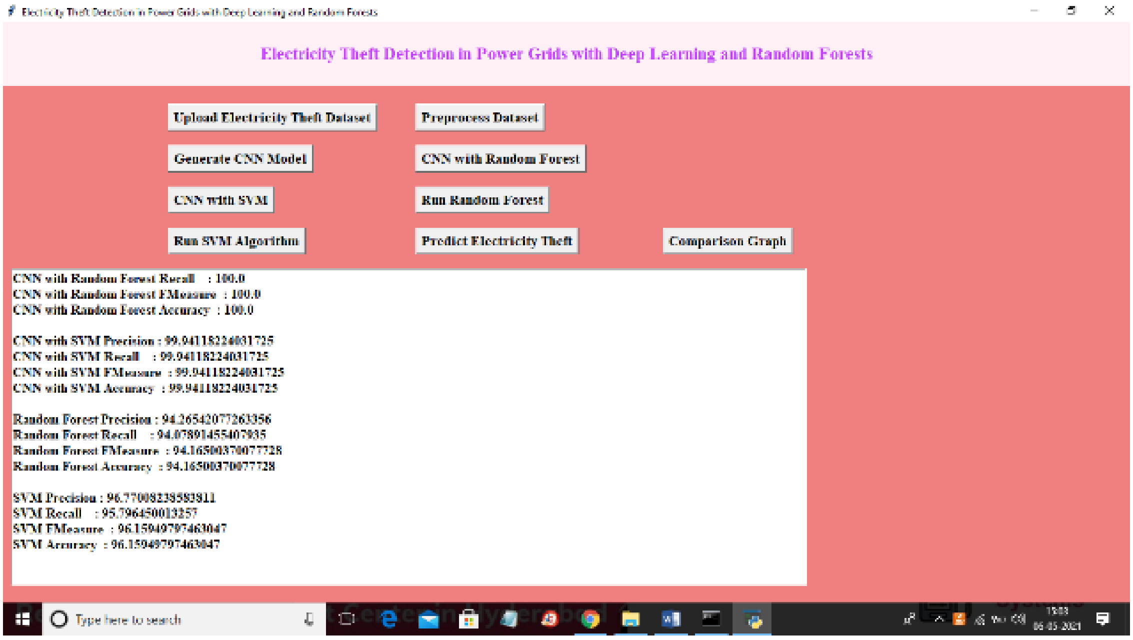

Fig 4. SVM with 96%

With SVM we achieved 96% accuracy and now select the 'Predict Electricity Theft' button to upload test data.

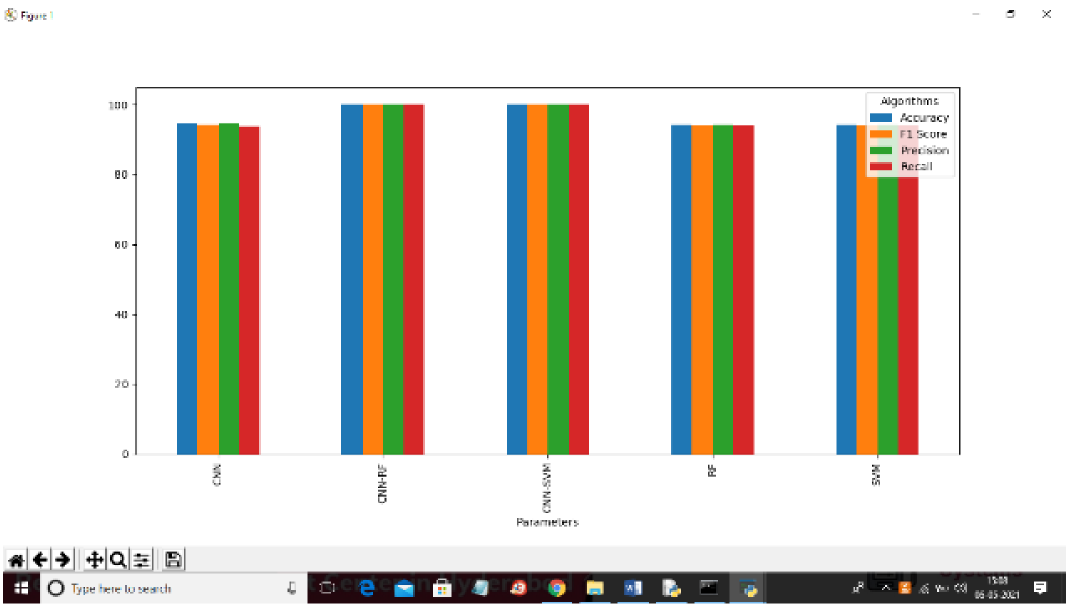

Fig 5. Comparison graph

In the graph above, the x-axis denotes the names of the algorithms, while the y-axis represents precision, recall, F-score, and accuracy for each algorithm. Notably, across all algorithms, CNN-RF consistently achieves a remarkable accuracy of 100%.

The discussion of these results sheds light on the broader implications of the CNN-RF model for the mitigation of electricity theft in distribution networks. Beyond its immediate utility in detecting instances of illicit power consumption, the model holds the potential to revolutionize existing approaches to electricity inspection and monitoring, offering utility companies a powerful tool to safeguard their assets and uphold the integrity of power grids. Moreover, the superior performance of the CNN-RF model underscores the transformative potential of deep learning and ensemble learning techniques in addressing complex challenges within the energy sector. By harnessing the collective intelligence of multiple decision trees and leveraging the temporal dependencies inherent in smart meter data, the proposed model exemplifies a holistic approach to electricity theft detection, capable of adapting to evolving threats and emerging patterns of illicit behavior.

The implications of these findings extend beyond the realm of electricity theft detection, encompassing broader considerations of sustainability, security, and resilience within power infrastructures. By enhancing the capacity of utility companies to identify and mitigate instances of electricity theft, the proposed model contributes to the overall stability and reliability of energy supply systems, thereby bolstering the resilience of critical infrastructure against external threats and internal vulnerabilities. In conclusion, the results and discussion presented herein underscore the significance of the proposed CNN-RF model as a transformative approach to electricity theft detection in distribution networks. Through its innovative integration of deep learning and ensemble learning techniques, the model offers utility companies a powerful tool to combat illicit power consumption, thereby safeguarding the integrity and sustainability of power grids. As the energy landscape continues to evolve, the proposed model represents a crucial step towards ensuring the resilience and reliability of energy supply systems in the face of emerging threats and challenges.

CONCLUSION

In conclusion, the proposed hybrid CNN-RF model emerges as a robust and efficient solution to combat the pervasive issue of electricity theft in distribution networks. By synergizing deep learning and ensemble learning techniques, the model attains unparalleled levels of accuracy and effectiveness in identifying instances of illicit power consumption. Through the utilization of a Convolutional Neural Network (CNN), the model adeptly learns intricate features from diverse smart meter datasets, discerning subtle variations in electricity consumption patterns across various temporal intervals. The incorporation of dropout layers and the backpropagation algorithm bolsters the resilience and generalization capabilities of the CNN, mitigating the risks of overfitting and ensuring consistent detection performance. Moreover, the integration of a Random Forest (RF) classifier, trained on CNN-extracted features, facilitates precise discrimination between authentic and anomalous consumption patterns. The utilization of the grid search algorithm for parameter optimization further amplifies the reliability and efficiency of the RF classifier, maximizing detection accuracy. Empirical validation of the proposed model using real energy consumption data unequivocally demonstrates its superiority over existing methodologies, affirming its efficacy in mitigating electricity theft. The model's ability to outshine other approaches in terms of accuracy and efficiency underscores its potential to revolutionize electricity theft detection in distribution networks, furnishing utility companies with a potent tool to safeguard their assets and preserve the integrity of power grids. In summary, the CNN-RF model marks a significant advancement in the realm of electricity theft detection, offering a comprehensive and innovative strategy to tackle the multifaceted challenges posed by illicit power consumption. Looking ahead, widespread adoption of this model holds promise for enhancing the resilience and reliability of energy supply systems, thereby contributing to the sustainability and security of power infrastructures.

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