Synthetic Minority Oversampling Technique Enhanced Machine Learning Models for Energy Theft Detection

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Abstract—Electricity theft poses significant challenges to utility companies worldwide, resulting in substantial financial losses. This study addresses the problem by leveraging machine learning algorithms to detect energy theft in smart grids. The insufficiency of data on theft conditions and the imbalance of datasets have always hindered the precise identification of fraudulent activity. To mitigate these challenges, we curated a dataset from the Open Energy Data Initiative, which encompasses sixteen consumer categories and six theft conditions. Our approach focuses on using the Synthetic Minority Oversampling Technique (SMOTE) to address class imbalance by generating synthetic samples for minority classes. We conducted a comparative analysis of various machine learning based classification algorithms, including K-Nearest Neighbors (KNN), Decision Tree, Random Forest (RF), Bagging with RF, and Ensemble Learning, and observed the results before and after the implementation of SMOTE on the dataset. We find that SMOTE demonstrates its most significant impact on classifying the most challenging classes within the dataset. In particular, it shows improvements of 57.00%, 37.88%, and 36.88,% for Class 6, Class 1, and Class 3, respectively, with the KNN algorithm. Other algorithms also indicate significant increments in terms of accuracy, kappa, F1-score, and AUC metrics in detecting fraudulent activity. Overall, this research contributes to advancing energy security by highlighting the importance of robust theft detection frameworks for safeguarding energy distribution systems.

Index Terms—Electricity Theft, Machine Learning, Smart Grids, Ensemble, Algorithm, Class Imbalance

I. Introduction

The widespread issue of electricity theft, characterized by unauthorized consumption bypassing payment, imposes substantial financial burdens on utility companies globally, with estimated annual losses surpassing $96 billion [1]. The advent of smart grids and Advanced Metering Infrastructure (AMI) presents an opportunity to utilize machine learning (ML) techniques for analyzing smart meter data to detect anomalies indicative of electricity theft [2].

Deep learning models and optimization techniques have shown promising results in analyzing power systems [3] and renewable energy [4]. So involving deep learning in Energy theft detection can help in detecting anomalies and patterns that traditional methods might miss. It begins with the pre-processing and feature engineering of smart meter data to extract attributes distinguishing standard from abnormal usage patterns. To mitigate the disparity in data distribution between legitimate and fraudulent instances, various sampling strategies are employed. Key contributions of this research include aggregating a dataset from publicly available smart meter readings representing diverse consumer categories, employing tailored data preprocessing, feature engineering, and sampling techniques for electricity theft detection, and assessing both machine learning and ensemble algorithms for classifying electricity theft across multiple categories. Model performance is comprehensively evaluated using rigorous metrics such as accuracy and F1-score.

The remainder of the paper is organized as follows: Section 2 provides a literature overview on ML-based electricity theft detection. Section 3 details the dataset, preprocessing steps, and methodologies employed. Section 4 analyzes model performance across various metrics. The paper concludes in Section 5, presenting conclusions and avenues for future research.

The rise of smart grids marks a transformative shift in the energy sector toward greater efficiency and reliability. However, this digital evolution also brings challenges such as energy theft, leading to significant economic losses and grid inefficiencies [5]. Traditional theft detection approaches often fall short of addressing the complex data patterns and anomalies inherent in smart grid systems. This study aims to overcome these challenges by harnessing ML techniques to enhance the accuracy of theft detection and fortify system integrity. Notably, our investigation reveals that integrating the K-Nearest Neighbors algorithm with the Synthetic Minority Over-sampling Technique (SMOTE) to mitigate class imbalance demonstrates exceptional proficiency in identifying abnormal consumption behaviors indicative of energy theft [6].

II. Background Study

The integration of Machine Learning (ML) techniques in electricity theft detection within smart grid systems addresses the limitations of traditional methods while leveraging advanced data analytics [7] [8] [9]. Smart meters within the Smart Grid framework enable precise monitoring and management of energy consumption, enhancing grid efficiency and resilience [10] [11]. However, the proliferation of smart metering systems has amplified the challenge of energy theft, resulting in substantial financial losses and compromising grid safety and reliability [12][13].

To address these challenges, there is a growing emphasis on leveraging ML techniques for more effective theft detection. Traditional methods, such as statistical techniques [14] and conventional data analysis algorithms, have shown limitations in adapting to the dynamic and complex nature of smart grid data, often leading to low accuracy in theft detection [15]. In contrast, Supervised [16] and Unsupervised ML algorithms, including extreme learning machines (ELM), and deep learning approaches like Convolutional Neural Networks (CNN) [17], Multimodel Transformers [18] and Long Short-Term Memory (LSTM) networks [19], have demonstrated superior performance by effectively capturing and analyzing intricate patterns associated with energy theft [20].

The application of CNNs and RNNs extends beyond traditional uses, showcasing effectiveness in analyzing time-series data and pattern recognition within energy systems, highlighting their adaptability and potential for energy-efficient computing [21] [22]. Similarly, Random Forest (RF) algorithms, particularly when combined with Synthetic Minority Over-sampling Technique (SMOTE), have proven effective in handling imbalanced datasets, a common challenge in theft detection, by improving classification performance through the generation of synthetic samples in the minority class [23] [24].

Despite these advancements, challenges persist, including the reliance on large, labeled datasets and substantial computational resources for deep learning models [25], and variability in the effectiveness of techniques like SMOTE based on dataset characteristics [26]. Other approaches, such as Stacked Machine and Deep Learning models, Adaptive Boosting, and Adaptive Random Forest, offer unique advantages but are also subject to limitations related to feature extraction, hyperparameter optimization, and the choice of optimization algorithms [27].

In conclusion, the transition towards ML-based theft detection in smart grids represents a significant advancement in addressing energy theft challenges. While each ML technique has unique strengths and limitations, careful algorithm selection should consider dataset characteristics and desired performance metrics. Future research should focus on overcoming existing barriers, exploring hybrid model fusion, and enhancing the adaptability and efficacy of ML techniques in practical scenarios.

III. METHODOLOGY

A. Dataset Description

The dataset utilized in this study was obtained from the Open Energy Data Initiative (OEDI) platform, a renowned repository of energy research datasets sourced from various programs, offices, and national laboratories under the U.S. Department of Energy [28]. This dataset encompasses comprehensive energy consumption data across diverse consumer types, collected over a year at hourly intervals.

1) Origin and Composition: The dataset, originally sourced from OEDI, has been refined to facilitate machine learning-based detection of fraudulent activities within smart grids[29].

TABLE I
GENERAL STATISTICS OF THE DATASET

Item	Numbers
Total number of instances	560,640
Number of columns	12
Number of features	11
Number of numerical features	10
Number of categorical features	1
Label encoding technique	IE*
Number of consumer types	16
Number of instances per consumer type	35,040

TABLE II
LIST OF CONSUMER TYPES

SN*	Customer Type	SN*	Customer Type
1	FullServiceRestaurant	9	Warehouse
2	Hospital	10	SecondarySchool
3	LargeHotel	11	SmallHotel
4	LargeOffice	12	SmallOffice
5	MediumOffice	13	Stand-aloneRetail
6	MidriseApartment	14	StripMall
7	PrimarySchool	15	SuperMarket
8	OutPatient	16	QuickServiceRestaurant

TABLE III
STATISTICAL NUMBERS FOR EACH CLASS

CN*	Class name	Number of instances
1	Normal	331,824
2	Theft1	51,083
3	Theft2	22,958
4	Theft3	44,349
5	Theft4	41,460
6	Theft5	33,553
7	Theft6	35,413

*IE stands for Integer Encoding Technique.
*CN stands for the class number.
*SN stands for the sequence number.

TABLE IV
FEATURES INFORMATION

Feature Name	Type
Electricity:Facility [kW](Hourly)	Float
Fans:Electricity [kW](Hourly)	Float
Cooling:Electricity [kW](Hourly)	Float
Heating:Electricity [kW](Hourly)	Float
InteriorLights:Electricity [kW](Hourly)	Float
InteriorEquipment:Electricity [kW](Hourly)	Float
Gas:Facility [kW](Hourly)	Float
Heating:Gas [kW](Hourly)	Float
InteriorEquipment:Gas [kW](Hourly)	Float
WaterHeater:WaterSystems:Gas [kW](Hourly)	Float
ConsumerType	String

It includes six distinct fraud scenarios mirroring different methods of electricity theft and covers sixteen consumer categories, representing various establishments such as restaurants, warehouses, hospitals, and schools.

2) Feature Representation: The dataset is feature-rich, capturing nuanced aspects of energy consumption patterns through numerical and categorical attributes. Features include electricity consumption metrics across facility components like cooling, heating, lighting, and equipment.The dataset contains a total of 560,640 instances distributed across 12 columns.
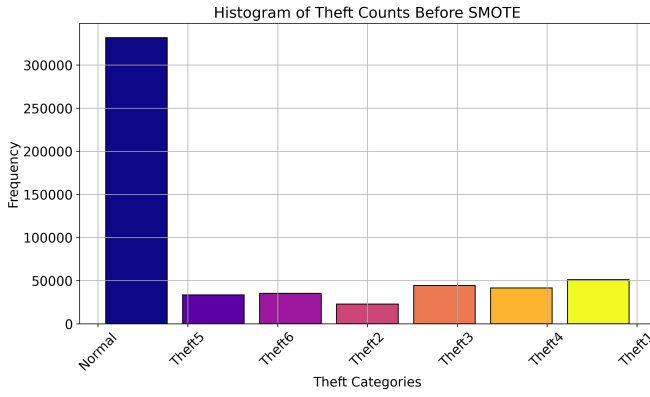
Fig. 1. Histogram of normal condition and different types of theft count. As can be seen from the figure, compared to the number of normal instances, the number of different types of theft instances is significantly low
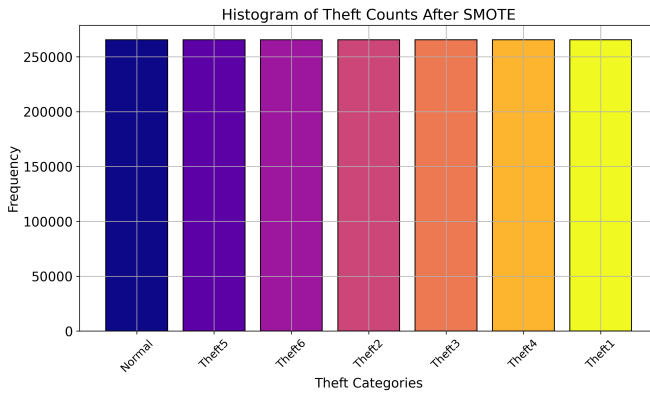

Fig. 2. Histogram different types of theft count after applying SMOTE. The class imbalance issue is fixed by creating synthetic data using SMOTE. All the numbers for the classes are now same.

Among these columns, 11 represent distinct features, with 10 being numerical and one categorical. The dataset displays 16 distinct consumer types, such as restaurants, hospitals, hotels, offices, schools, retail outlets etc., with an equal distribution of instances per consumer type, with each type containing 35,040 instances.

3) Fraud Detection Context: Fraud-related scenarios, labeled as theft1 through theft6, are integrated into the dataset to facilitate advanced anomaly detection and fraud mitigation strategies within smart grid environments. In summary, Researchers can leverage this dataset to uncover insights and develop robust frameworks for combating fraudulent activities within energy distribution networks.

B. SMOTE

SMOTE (Synthetic Minority Over-sampling Technique) is an advanced over-sampling approach used to address class imbalance in machine learning datasets. This imbalance typically occurs when one class (the majority class) significantly outweighs another (the minority class), leading to models that are biased towards the majority class. SMOTE addresses this

issue by creating synthetic examples of the minority class, rather than simply duplicating existing instances[29].

1) Why Use SMOTE: SMOTE is essential in machine learning when the dataset is imbalanced. Traditional algorithms may not learn effectively from the minority class due to its underrepresentation, which can result in models that fail to identify this class accurately. By enhancing the representation of the minority class, SMOTE improves the model's training phase and its ability to classify instances of the minority class correctly[30].

2) Steps of the SMOTE Algorithm: [31]

- Select a Minority Class Instance: Start by choosing a sample from the minority class.
- Identify Nearest Neighbors: Find its k-nearest neighbors in the feature space.
- Random Neighbor Selection: Randomly pick one of these neighbors.
- Synthetic Instance Generation: Create a new synthetic instance along the line segment connecting the selected minority class instance with its chosen neighbor.

This process not only balances the class distribution within the dataset but also enhances the generalization capabilities of the model. By interpolating among existing minority class instances, SMOTE fosters a more diverse dataset, thereby reducing the risk of overfitting to the minority class[29].

3) Mathematical Representation of SMOTE: The creation of a synthetic sample involves linear interpolation between a minority class sample x_i and one of its k-nearest neighbors x_{zi}. The synthetic sample x_{new} is calculated using the equation:

$x_{\text{new}} = x_i + \lambda \cdot (x_{zi} - x_i)$

where λ is a random number between 0 and 1. This formula demonstrates how new instances are generated by combining features of existing data points, preserving the feature space's underlying relationships and enhancing the informational continuity of the dataset[30].

4) Benefits of SMOTE:

- Addressing Class Imbalance In imbalanced datasets, where one class (majority class) significantly outweighs the other (minority class), biased models favoring the majority class may result. SMOTE resolves this issue by generating synthetic samples for the minority class, balancing the distribution, and enhancing model performance [29].
- Improved Generalization By creating synthetic samples via interpolation among existing minority class instances, SMOTE increases dataset diversity, fostering better model generalization and reducing the risk of overfitting to the minority class [29].
- Preservation of Information SMOTE generates synthetic samples based on feature space, focusing on feature relationships to preserve underlying dataset information while balancing class distribution [29].
- Enhanced Performance Studies demonstrate that SMOTE significantly boosts classifier performance on imbalanced

	KNN			DT			RF			Bagging			Ensemble Learning		
	Before	After	Change	Before	After	Change	Before	After	Change	Before	After	Change	Before	After	Change
Class 0	93.12	100	6.88	97.03	95.08	-1.95	94.23	94.03	-0.2	93.87	94.11	0.24	93.78	95.69	1.91
Class 1	60.23	98.11	37.88	74.21	92.19	17.98	75.16	95.80	20.64	72.10	94.86	22.76	74.76	97.84	23.08
Class 2	100.00	100.0	0	100	100	0	100	100	0.00	100	100	0	100	100	0
Class 3	61.24	98.12	36.88	69.09	91.05	21.96	78.01	92.02	14.01	75.89	90.58	14.69	74.93	95.76	20.83
Class 4	74.35	98.65	24.3	88.13	96.11	7.98	87.31	96.97	9.66	84.78	94.68	9.90	86.82	98.65	11.83
Class 5	88.43	98.75	10.32	96.80	100.00	3.2	97.11	100.00	2.89	95.21	100.00	4.79	96.45	99.68	3.23
Class 6	38.23	95.23	57.00	55.24	88.89	33.65	28.19	91.79	63.6	40.16	92.67	52.51	46.23	94.86	48.63

	Accuracy			F1 Score			Kappa			AUC		
	Before	After	Change	Before	After	Change	Before	After	Change	Before	After	Change
KNN	84.85	97.68	12.83	82.78	97.68	14.9	74.57	97.79	23.22	90.87	98.79	7.92
DT	89.40	94.69	5.29	89.41	94.68	5.27	82.96	93.80	10.84	90.59	96.90	6.31
RF	87.90	95.75	7.85	87.05	95.72	8.67	80.23	95.04	14.81	96.72	99.73	3.01
Bagging	88.67	94.78	6.11	86.78	94.78	8.00	81.69	94.88	13.19	95.45	99.85	3.4
Ensemble	89.21	97.7	8.49	88.14	97.70	9.56	82.23	97.32	15.09	97.30	99.94	2.64

datasets, making it invaluable for handling such challenges [29].

- Versatility SMOTE's success spans various domains and has inspired the development of new approaches for tackling class imbalance. Its simplicity, robustness, and effectiveness have made it a popular choice among researchers and practitioners working with imbalanced datasets[29].

In summary, SMOTE is favored for addressing class imbalance, improving generalization, enhancing performance, and offering versatility in handling data challenges.

IV. EXPERIMENTS AND RESULTS

In the experimental phase of our study, we utilized various classification algorithms implemented through the Python sklearn package to explore the effectiveness of the Synthetic Minority Oversampling Technique (SMOTE) in improving the detection of electricity theft. The focus was particularly on K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), Bagging, and Ensemble Learning methods. TABLE V compares the classification accuracy using these algorithms. This comparison was evaluated under the challenging conditions posed by an imbalanced dataset characterizing different classes of electricity theft.

Initially, our models struggled to accurately classify particularly problematic classes—namely Class 1, Class 3, and most notably, Class 6, which proved to be the most challenging scenario. Class 0, representing normal conditions, was consistently identified with high accuracy, demonstrating the initial competence of our models in recognizing standard patterns of electricity usage.

Upon the application of SMOTE, a dramatic transformation was observed. The accuracy improvements for Class 6 were particularly striking, illustrating the power of SMOTE in leveling the playing field for minority classes. KNN showed the most significant enhancement, with accuracy jumping by 57.00%, while RF also showed a remarkable increase of 63.00%. Similarly, Decision Tree, Bagging, and Ensemble Learning methods exhibited substantial improvements with increases of 33.65%, 52.51%, and 48.63% respectively.

To provide a comprehensive view of the impact of SMOTE across all models, we compiled the changes in performance metrics such as accuracy, F1 score, kappa, and AUC into TABLE VI. The results were telling: post-SMOTE, all models not only surpassed the 90% accuracy threshold but also showed notable improvements in F1 scores, which ranged from increases of 5.27% to 14.9%. The Kappa score, a metric that quantifies the agreement between predicted and actual class labels, along with the AUC, which assesses the ability of a classifier to discriminate between classes, both confirmed the enhanced capability of our models to accurately identify and classify instances of electricity theft.

KNN, in particular, stood out not only for its improved accuracy but also for its efficiency, taking the least amount of time to run among the tested algorithms. This combination of high performance and efficiency underscores the suitability of KNN, augmented by SMOTE, for real-world applications where rapid and reliable theft detection is crucial.

These experimental results vividly demonstrate how SMOTE can dramatically boost the performance of machine learning models dealing with imbalanced data, thereby significantly enhancing their practical utility in detecting complex patterns such as those presented by electricity theft in smart grids. This narrative of transformation, from initial struggles to remarkable achievements in classification accuracy, paints a compelling story of the potential of SMOTE in advancing the field of anomaly detection within machine learning.

V. CONCLUSION & FUTURE WORK

This study underscores the impactful role of machine learning, particularly when combined with the Synthetic Minority

Oversampling Technique (SMOTE), in enhancing the detection of electricity theft within smart grids. Through strategic SMOTE utilization, our study effectively balanced imbalanced datasets, thereby bolstering model accuracy in identifying instances of theft. This method, alongside rigorous data preprocessing and judicious algorithm selection, forms a robust defense mechanism for utility companies, shielding both them and their consumers from fraudulent activities.

Looking ahead, the machine learning landscape in electricity theft detection faces challenges. These include the reliance on extensive, well-labeled datasets and significant computational resources, hindering widespread adoption. Additionally, the efficacy of SMOTE and similar techniques can vary based on data characteristics and specific scenarios.

To surmount these challenges, future research should focus on developing hybrid models. These models would integrate diverse machine learning approaches, leveraging their respective strengths to create adaptable and efficient systems tailored to smart grid environments. Such advancements are essential for ensuring the intelligence and resilience of smart grid systems against evolving threats of electricity theft. Embracing more sophisticated, hybrid machine learning frameworks promises to fortify energy infrastructure in the digital age.

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