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Article

# Energy Theft Detection in IoT-based Smart Grid Using Deep Learning

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**Abstract:** The development of smart devices and the integration of Internet of Things (IoT) technology into modern energy systems have enabled real-time acquisition of high-frequency smart meter data, which supports the development of sustainable and efficient power grids. This real time data monitoring enhances operational efficiency and optimal utilization of energy. However, these smart devices, such as smart meters, increase the complexity of the system, which introduces challenges in identifying anomalies such as energy theft, meter malfunctions, and irregular consumption patterns, which negatively impact energy sustainability. Energy theft is one of the major concerns because it leads to unnecessary non-technical losses and inefficient utilization of electrical resources. This paper presents a method to detect energy theft with the help of machine learning and deep learning techniques. The techniques implemented are Support Vector Machine (SVM) and Convolutional Neural Network (CNN). These techniques are used to analyze real-world energy consumption patterns. The available dataset was imbalanced due to the scarcity of energy theft cases. To address the imbalance in smart meter datasets, synthetic data is generated by assuming certain conditions that may represent the energy theft scenarios. The models that are proposed here are trained on one year data taken from smart meters to accurately learn and predict load patterns reflecting actual consumer behaviour. To validate these proposed models and to evaluate the performance of models (SVM & CNN), quality indices such as the confusion matrix, accuracy, precision, and recall metrics are utilized. The experimental results demonstrate that the CNN model presents better results than the SVM, particularly in detecting minority classes associated with energy theft. The accuracy observed for the CNN model is 98%, and a recall of 87 %. These results validate the CNN model for detecting energy theft cases, which is actually a non-technical loss, hence supporting sustainable, reliable, and environmentally responsible smart grid operations.

**Keywords:** . Anomaly Detection, Sustainable Energy System, Smart Grid, Deep Learning, Convolution Neural Network, Energy Theft

## 1. Introduction

For a sustainable smart grid, two-way communication is possible because of the integration of IoT, which helps the system gain a deeper understanding of energy consumption and load patterns. This understanding of energy consumption helps in coordinating demand and supply management, improving load forecasting, and informed decision-making, which are essential for improving grid reliability, power quality, and overall energy efficiency. By enabling the implementation of adaptive control and real-time monitoring, smart grids play a vital role in promoting sustainability, reducing energy losses, and enabling the effective integration of renewable energy sources.

Moreover, the usage of smart devices such as smart meters and sensors at the consumer end makes consumers more vigilant in order to consume energy responsibly. This responsible behaviour of consumers also supports long-term environmental goals.

These capabilities play an important role in reducing electricity wastage and improving the utilization of existing infrastructure.

However, in spite of the above-mentioned benefits of sustainable smart grids, there are lots of challenges, such as data security and reliability, energy theft, technological interoperability, and the management of large-scale heterogeneous data. These challenges can reduce energy efficiency and lead to non-technical losses, thereby affecting the sustainability of power systems. Consequently, efficient data analysis and intelligent monitoring are essential to improve grid performance, reduce losses, and support sustainable energy systems.

### *1.1 Problem Statement*

Although smart meter data is available, there is still a deficiency of a robust and scalable framework to detect anomalies and analyze energy consumption patterns in sustainable energy systems. The existing approaches suffer from various shortcomings, such as the complexity of computation, poor scalability and insufficient detection accuracy. These shortcomings cause a hitch in their practical deployment. Additionally, there is a lack of integrated frameworks that combine both anomaly detection, i.e., energy theft in our case and demand supply management. This affects grid efficiency, reliability and long-term sustainability of smart grid operations.

This work aims to address the identified gaps by achieving the following objectives

- To observe the energy consumption patterns of a real system in order to optimize demand-supply management and enable load balancing.
- To develop and apply deep learning models for detecting energy theft in the real power consumption data.
- To evaluate and compare the performance of machine learning and deep learning techniques in terms of detection accuracy, computational efficiency, and suitability for sustainable smart grid applications.

The outline of this paper is as follows:

- **Section II** presents the literature review to explore the existing methodology and the gap in the existing techniques.
- **Section III** represents the methodology adopted in the present work. Details of machine learning and deep learning models, such as design and development, are presented.
- **Section IV** shows the results obtained, and the discussion of result is presented in this section.
- **Section V** present Conclusion, contributions of the work and the future scope.

## 2. Literature Review

Numerous fields have heavily used Anomaly detection techniques, including smart grid systems. Present-day approaches are of three major classifications: statistical techniques, machine learning models, and deep learning architectures. Rule-based systems and clustering algorithms used to identify outliers are often involved in statistical methods. Anomaly detection can be done using various ML techniques, such as Support Vector Machines (SVM) and Isolation Forest (IF)

In [1], an Isolated Forest Model was analysed using smart grid data by Shabad et al. (2021), which leverages multiple decision trees and isolates outliers from standard observations. For processing and analysing time-series data, deep learning approaches such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have been proven effective. Moreover, in [2], a machine learning and deep learning hybrid model has been presented by authors Y Liang and Nikhil Vankayalapati(2023). It was applied to find anomalies in IoT datasets for cybersecurity applications. In this study, the application of SVM and CNNs for machine learning and deep learning, respectively, has been discussed, demonstrating their efficacy in anomaly detection tasks

In [3] by Agnieszka Nowak-Brzezinska and Czesław Hory (2020) and in [4] by Jinbo Li et al. (2021), traditional methods like the rule-based systems and classical clustering algorithms have been applied, though they significantly struggle with scalability, adaptability, and computational efficiency required for processing large-scale IoT datasets.

Thus, advanced deep learning methods are required to overcome these limitations and to address the complexities of smart meter data. However, an increase in the number of IoT connections increases the security concern, as more cyber-attacks on IoT devices are probable. These data security concerns have been discussed in [5] by Pinto Neto et al. (2023)

In [6] by H. Zheng et al.(2024), recent advances in deep learning, especially CNNs, have been proven extremely effective in handling large-scale time-series data.

One study highlighted CNN's ability to detect non-linear patterns in a dynamic environment, like financial markets. Though in smart grid data, identical non-linear patterns exist, these findings justify deep learning model application in analysing the model's effectiveness in detecting anomalies in smart grid applications.

This electricity theft using deep learning literature review brought light to multiple methodologies adopted by researchers in recent years. The studies employ methods of different ML and DL models, datasets, and performance metrics to improve detection accuracy.

A CNN-LSTM-based approach was applied in 2019 by Hasan et al. to analyse electricity theft utilising the State Grid Corporation of China dataset, which achieved an accuracy of 89%[7]. Correspondingly, the accuracy was improved to 95% by leveraging an attention LSTM Inception model on the same dataset in 2022 by Munawar et al.[8]. A similar study used the Bayesian and adaptive moment estimation techniques to optimise hyperparameters, which gave an accuracy of 91.8% by combining frequency and time-domain analysis in [9] by Leloko et al. 2019.

Recent literature highlights the use of hybrid models to improve accuracy. In 2024, CNN was combined with traditional methods by Gunduz and Das and brought the accuracy up to 95.34% using the ISSDA dataset[10]. A study by Zheng et al. (2024) used time-series analysis [5] with LSTM and CNN-BiLSTM hybrid models, which, instead of reporting performance through accuracy, reported MSE and MAPE, demonstrating an alternative evaluation approach. Alromih et al. (2021) implemented a neural network approach using the Grid Lab D Tool and were successful in achieving 93% accuracy [11].

Moreover, some researchers explored alternative applications of deep learning in power systems. Belhaiza and Al-Abdallah (2024) utilised ANN for load forecasting and compared three statistical methods on Toronto datasets [12, 13].

Another study by Qia et al. (2023) explored semi-supervised learning to detect electricity theft, achieving varying accuracy levels for different attack types using Irish business and residential data [14]. In [15], Ashraf Ullaf et al. proposed a combined DNN to address the electricity theft problem by utilising intelligent antenna-based energy meters.

Extensive research has been carried out on datasets to boost the performance of fraud detection models. Many researchers have inserted fraudulent data into legitimate consumption data to simulate real-world attack scenarios and improve model robustness.

A Deep Neural Network Model for classification was used as presented by M.Z. Gunduz et al. (2023)[16], to distinguish legitimate and fraudulent data of energy consumption patterns. High performance and accuracy were shown by the presented models. Multiple experiments using a real-world consumption dataset comprising over 2,000 subjects were conducted. To simulate fraudulent activities, two different types of data vectors were mixed with an honest dataset to create manipulated data. The model achieved an accuracy of 97.4% being trained using the K-fold cross-validation technique.

A thorough analysis of data-driven approaches was presented in [17] by Mahmoud M. Badr et al. (2023) for catching electricity fraud in smart metering systems. Multiple machine learning and deep learning techniques were studied for detecting fraud, highlighting their advantages and limitations.

An innovative method was introduced by Ahmed T. El-Toukhy et al. (2023) in [18] for detecting electricity theft via four different scenarios. Firstly, Deep Q-Network (DQN) and Double Deep Q-Network (DDQN) architectures were used with different deep neural network structures to create a holistic detection model. Second, the holistic detector was trained to create customised detection models for new users, which improved the detection ability and mitigated zero-day attacks. Third, the model considered variations in the energy consumption for the available users. And finally, the challenges of emerging cyber-attacks were addressed in the fourth condition. Intense research and experiments validated the proposed deep reinforcement learning (DRL)-based approach's effectiveness, showing its capabilities of enhancing electricity theft detection, adopting the new energy patterns, and successfully identifying the emerging cyber threats. In [19], Mileta et al. discussed artificial intelligence applications in detecting energy theft in distribution networks, which established the efficiency of AI-based methods in reducing non-technical losses. In addition to this, anomaly detection in smart grids was addressed in [20] using advanced data-driven techniques, which sheds light on the role of intelligent analytics in enhancing grid reliability and sustainable operation.

Literature has highlighted renewable energy integrated smart grids in attaining sustainable and efficient power systems. An IoT-based green smart grid structure was proposed by Rania et al. in [21], which integrated solar energy and distributed edge computing. which substantially improved the reliability and energy efficiency, with a reduction of 24.3% in energy consumption as compared to the traditional grids. [22] These findings highlight the potential of intelligent monitoring and control in supporting sustainable smart grid operations.

Altogether, the research highlights the importance of hybrid DL models, including CNN-LSTM, Attention LSTM Inception, and CNN-BiLSTM, which have consistently proved to give high accuracy in electricity theft detection. [23] The dataset selection also has a significant role in achieving good results, with datasets from the State Grid Corporation of China, ISSDA, and Irish data being commonly used [24].

This work is carried out with a new dataset, CEEW, which is explained in detail in the subsequent Section. [25]

## 3. Methodology

To get the anomaly detection model to perform reliably with high accuracy, the raw data is cleaned, and the preprocessing stage involves various important steps. The data set used for the present work is an Indian data set, which is honest consumption data of smart meters provided by the "Council on Energy, Environment and Water (CEEW)". The smart meter data collected from Mathura and Bareilly districts, with energy readings taken at 3-minute intervals. This data serves as the foundation to train the model to distinguish between honest and tampered energy consumption patterns. Figure 1 shows the workflow of the present work.

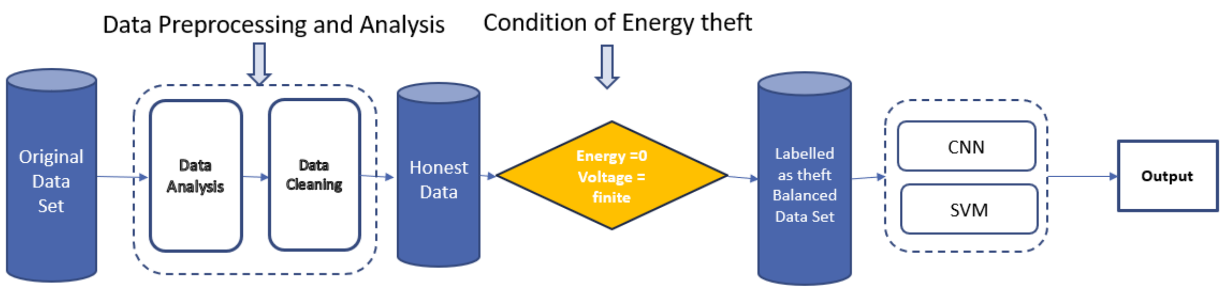


**Figure 1 : Workflow**

### *3.1 Data Preprocessing*

1. Firstly, the dataset was cleaned for null and missing values to ensure data quality and consistency.
2. A new column in excel file of the dataset is inserted, which represent new attribute 'Hour'. It is required to analyse the hourly energy consumption patterns.
3. Since the dataset involves time-series data, for a better understanding of the dataset date and time columns are separated.
4. Renaming of the column is done for better understanding, such as x_Timestamp is separated and changed to date and hour. The column t_kWh changed to energy.
5. Normalize the data.
6. To find the anomaly in the dataset, a condition was defined that represents the energy theft, although it may not be the actual condition of energy theft.

- It is assumed that if the voltage is finite, which represents that the electricity is available at the consumer end, but energy consumption shown by the smart meter is zero, we have assumed this condition as energy theft, and the output is labelled as 1.
- Other than the above condition, the output is labelled as 0, which represents no theft.

These steps are important to ensure that the dataset is now understandable and prepared for effective anomaly detection. With the help of the processed dataset load consumption pattern is observed to get the actual consumption pattern throughout the year as shown in figure 2. This curve illustrates the variation in electricity demand at various time zones. It also highlights the peak and low demand in the whole day and across different seasons. This analysis provides important information about seasonal electricity consumption and helps in understanding overall load behaviour. Figure 3 represents the load prediction by CNN model versus the actual power consumption.

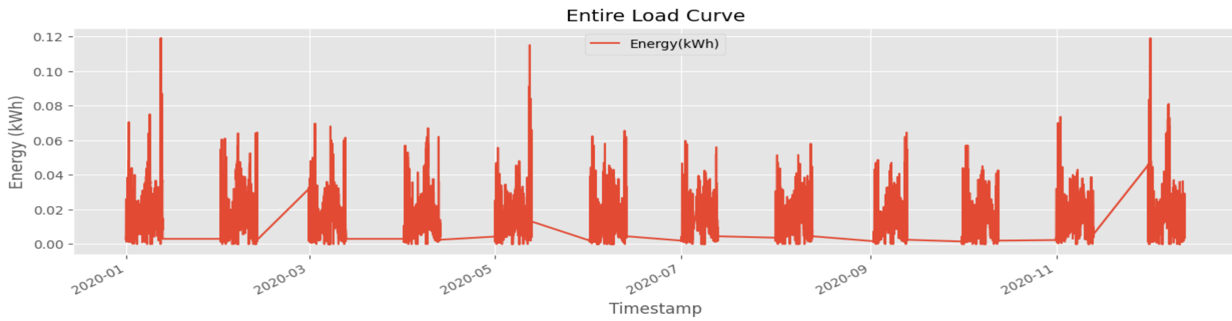


**Figure 2 : Entire Load Curve for one year**

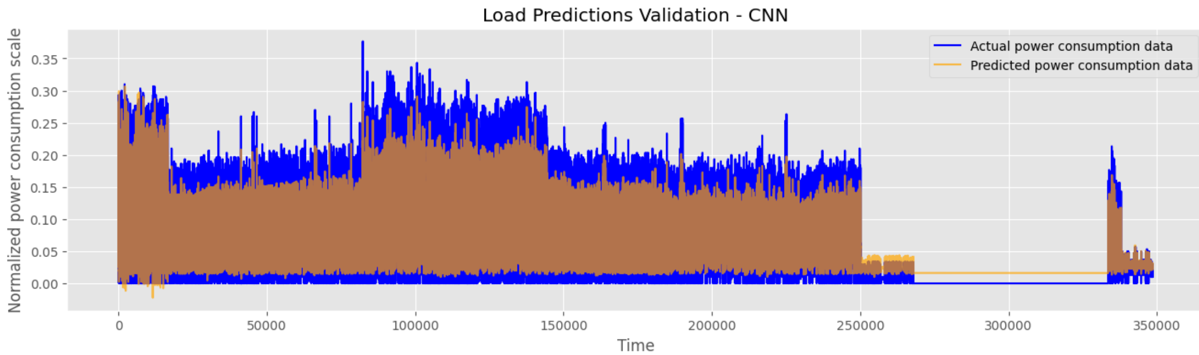


**Figure 3 :Load Prediction Vs Actual Consumption**

To enhance the accuracy of load forecasting, it is essential to analyze daily electricity load trends. This requires compressing the yearly dataset into a representative single-day profile. The process involves computing the average electricity consumption for each specific time of the day across the entire year.

For example, if we want to determine the energy consumption pattern at 10:00 AM daily, we have to take the average of the electricity consumption records at the same time throughout the year. In this way, we can compress the yearly electricity pattern in to daily electricity consumption pattern. This approach helps in capturing the overall pattern of electricity demand at various time zones of the day while minimizing the impact of short-term fluctuations.

The daily load curve as shown in figure 4, which resulted from averaging the data, represents the clear view of electricity consumption over a 24-hour period. This curve plays a crucial role in electricity demand and supply management by helping utilities and policymakers understand peak demand hours, identify periods of low consumption, and optimize resource allocation for efficient grid operation

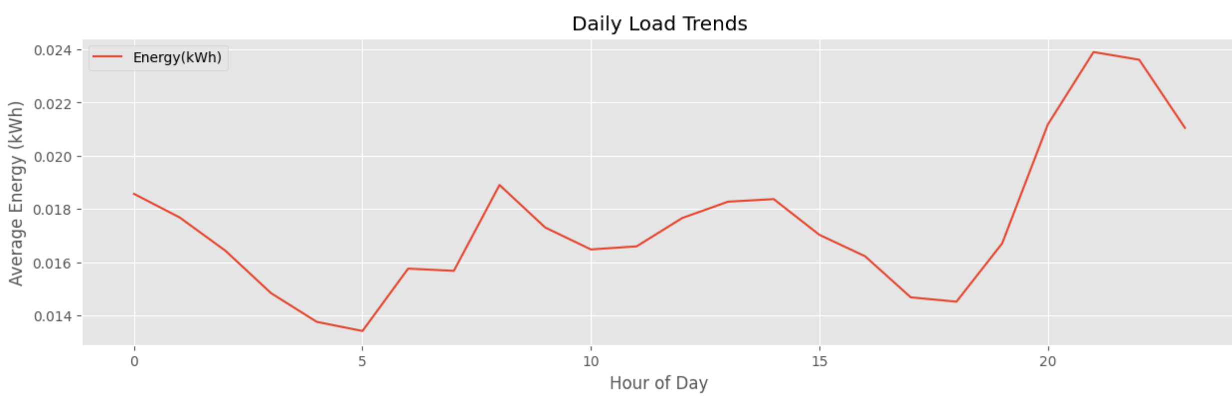


**Figure 4 : Daily Load Trends**

Now problem of data imbalance is solved by applying a data augmentation technique based on a domain-specific condition. Specifically, we identified instances in honest customer data where the voltage reading is finite, but the energy consumption is zero. Such instances are indicative of a potential theft scenario, according to the established anomaly condition. By labelling these instances as theft cases, we artificially increase the number of theft samples, thereby balancing the dataset. This approach leverages existing honest data to generate additional theft-like samples without synthetically creating data from unrelated distributions.

**RNN Model**

Initially, we developed an RNN model by ignoring anomalies. To train the model, the dataset is split into 70 and 30 ratio, 70% data is utilized for training and 30 % for testing purposes. The dataset consists of approximately 10 lakh (1,000,000) rows, out of which around 700,000 rows were used for training the model, and 300,000 rows were reserved for testing its performance.

**CNN model** was developed using the above dataset. The Relu function is activated.

**Model Architecture:**

1. **Support Vector Machine (SVM):**

Uses an RBF kernel.

Configured with C=1.0 and random state=42.

The SVM model was trained on features 'Voltage (V)' and 'Energy (kWh)'.

2. **Convolutional Neural Network (CNN):**

- The CNN is structured with: An input layer expecting sequential data, a convolutional layer , a max pooling layer, a dropout layer for regularization, a flatten layer to vectorize features and a dense output layer for regression (predicting energy consumption).
- The CNN model is compiled with the 'Adam' optimizer and 'MSE' loss function.
- Trained for 10 epochs with a batch size of 80.

## 4. Result & Discussion

The following are the results that are achieved by adjusting the threshold value for anomaly detection

**Evaluation metrics:** Confusion matrix, accuracy and precision

**Result achieved :**

CNN Model R2 Score: 0.7877212666195724

CNN Model MSE: 0.0007104518303173544

### *4.1 Model Performance Metrics*

**CNN Model**

The proposed CNN model was trained and tested on smart meter data. The final model was evaluated on the test dataset , table 4.1 represents the performance metrics:

**Table: 4.1 Performance Metrics**

| Metric | Score |
|---|---|
| Accuracy | 98% |
| Precision (Theft) | 90 % |
| Recall | 87% |
| F1- Score | 89 % |
| R2 Score | 0.78 |

The high accuracy (98%) indicates that the model correctly classifies most of the energy consumption patterns. However, to assess theft detection performance, precision, recall, and F1-score were analyzed specifically for the theft class.

### *4.2 Confusion Matrix Analysis*

Table 4.2 presents the confusion matrix of the CNN model

**Table 4.2 : Confusion Matrix(CNN Model)**

| | |
|---|---|
| **319341** | **2467** |
| **3372** | **23385** |

CNN Accuracy: 98%

The confusion matrix shows that the model has a high detection rate for theft cases, with 87% recall. The results demonstrate that the proposed CNN model is highly effective in detecting energy theft from smart meter data. The high precision (99%) indicates that when the model predicts theft, it is correct in most cases, reducing false alarms. The recall (87%) highlights the model's capability to identify the majority of theft cases.

The F1-score (89%) shows an optimal balance between precision and recall, making the model suitable for practical deployment in smart grid systems.

**SVM model**

Table 4.3 presents the confusion matrix for SVM model when applied to detect energy theft cases:

**Table 4.3 : Confusion Matrix (SVM Model)**

| | |
|---|---|
| **306939** | **0** |
| **7634** | **0** |

SVM Accuracy :97.57%

## 5. Conclusions

Comparing the performance of the SVM and CNN model, CNN proves to be a more reliable model to detect energy theft cases for the system where such incidents are rare. The model shows potential for providing support to utility companies for reducing non-technical losses and ensuring fair energy distribution due to its great performance. The detection of rare theft patterns can be improved further by fine-tuning and feature engineering, making this model robust for large-scale deployment.

A Convolutional Neural Network (CNN) model for detecting energy theft was illustrated in this work using high-frequency smart meter data. The model showed great accuracy of 98%, and an F1 score of 89% for theft detection, which makes this model an attractive approach for identifying fraudulent electricity usage.

The Challenges faced were due to the imbalance in the dataset. For the available dataset, the smart meter data predominantly covered honest consumption records, with fewer theft cases. Due to this, the model was only exposed to a limited set of theft patterns, impacting its generalisation ability. Despite these shortcomings, the model proved to be successful in recognising theft cases with high precision and recall, and proved its ability in distinguishing between normal and fraudulent consumption.

Furthermore, techniques like synthetic data generation and feature engineering can be explored in order to improve the model’s efficiency. This study sheds light on the effectiveness of advanced machine learning techniques in making sure that efficient and fair energy distribution takes place, ultimately aiding power utilities in reducing non-technical losses (NTL).

**Contributions of the Paper:**

1. The present study uses Indian data, which is a high-frequency smart meter dataset CEEW that, to the best of our knowledge, has not been previously employed by any other researcher in the domain. This provides fresh insights and a new benchmark for energy theft detection.

2. Unlike conventional methods, our approach leverages domain knowledge to identify instances where the voltage is finite and energy consumption is zero within honest customer data. Such instances are labeled as theft, allowing us to artificially balance the dataset, enhance model training, and improve detection performance.
3. Develops a high-accuracy CNN model achieving 98% accuracy, offering a practical solution for large-scale real-world deployment.

**Future Recommendation:** While the proposed CNN model has shown promising results, there are several areas for future improvement and research:

- Synthetic Data Generation:

Since real-world theft cases were limited, generating synthetic theft data using methods like GANs (Generative Adversarial Networks) or data augmentation techniques can enhance model robustness.

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