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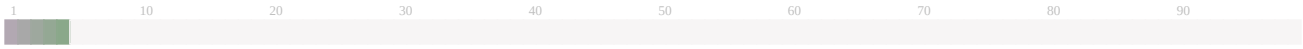

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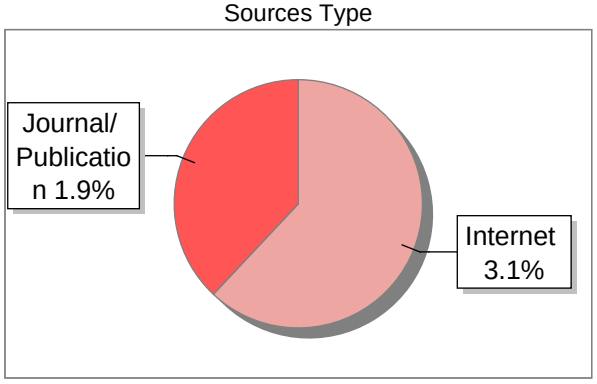

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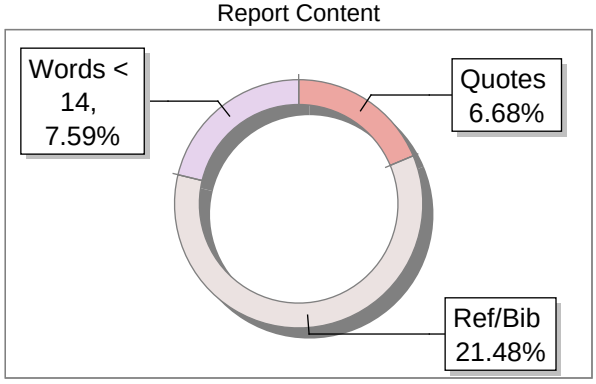

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Electricity Theft Detection using Machine Learning: A Comparative Study of Clustering, CART, SARSA, and KNN

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Abstract- Electricity theft continues to cause financial and operational challenges for smart grids. Manual detection methods are inefficient, prompting the need for automated solutions. This study compares four machine learning techniques—K-Means (unsupervised), CART (supervised), SARSA (reinforcement learning), and KNN (instance-based)—using the China Smart Meter dataset. After data preprocessing and feature extraction, these models were evaluated based on accuracy, ROC-AUC, and precision-recall. Results show CART had the best accuracy and clarity, while SARSA showed promise for real-time adaptability. KNN and K-Means had moderate success, though scalability remains an issue. Future work may explore hybrid models, attention mechanisms, and ensemble-based deployment strategies to enhance detection systems in smart grids.

Keywords: Electricity theft, Smart grid, Machine learning, K-Means, CART, SARSA, KNN, Anomaly detection, Ensemble methods, Real-time detection, Feature extraction, ROC-AUC, Hybrid models

I. INTRODUCTION

Electricity theft continues to be a significant global concern, imposing heavy economic burdens on power utilities and disrupting grid reliability. Traditional detection techniques such as physical inspections and manual audits often fall short, especially when dealing with sophisticated forms of non-technical losses (NTLs).

With the widespread deployment of smart grids and Advanced Metering Infrastructure (AMI), high-frequency energy usage data is now available through smart meters. This has paved the way for intelligent systems that can automatically identify suspicious consumption behavior. Machine learning (ML) techniques like Decision Trees [1], K-Nearest Neighbors (KNN) [2], reinforcement learning models like SARSA [3], and clustering-based anomaly detection have shown encouraging results in this domain.

Furthermore, the use of real-world datasets—such as the China State Grid dataset [4][5]—adds credibility to research efforts by reflecting actual usage patterns. This project focuses on leveraging multiple ML models to build a robust and efficient electricity theft detection system tailored for smart grid environments.

II. LITERATURE REVIEW

In recent studies, numerous machine learning strategies have been explored to detect electricity theft with improved accuracy and efficiency. Decision Tree classifiers, such as CART, have been utilized to classify usage patterns and flag anomalies based on consumption history [1][6]. These models are appreciated for their simplicity and interpretability.

KNN-based methods have also been applied in theft detection scenarios, benefiting from their ability to compare a consumer's behavior with similar usage profiles [2][7]. However, scalability and computational complexity remain concerns in large datasets. Clustering approaches such as K-Means and DBSCAN have been employed to discover underlying patterns and separate typical behavior from fraudulent cases [8][9].

To address dynamic behavior and delayed tampering, reinforcement learning algorithms like SARSA have been incorporated for adaptive learning and real-time decision-making [3][10]. These models adjust to new patterns over time, making them suitable for evolving grid environments.

Hybrid models combining oversampling (e.g., SMOTE) with ensemble techniques have also shown promise, enhancing detection rates by addressing data imbalance [11]. Some works have explored the integration of fuzzy logic or probabilistic models for better uncertainty handling in anomaly detection [12][13].

Furthermore, the use of real datasets, particularly the China State Grid and TNB smart meter datasets, has enabled benchmarking and validation of various models under realistic settings [4][5][14].

Performance metrics such as accuracy, precision, recall, and ROC-AUC are widely used to evaluate model effectiveness [15][16].

Other research has focused on comparing algorithms (e.g., logistic regression, Naïve Bayes, SVMs) to find trade-offs between interpretability and detection accuracy [17][18]. Recent advancements also involve deep learning and federated learning frameworks for distributed detection while preserving data privacy [19][20].

Collectively, these studies underscore the need for lightweight, accurate, and explainable systems to detect electricity theft effectively in modern power systems. The current work builds on these findings by evaluating CART, KNN, SARSA, and clustering-based models using real smart meter data.

III. Implementation

Model Selection

- Clustering (e.g., K-means, DBSCAN)
- CART (Classification and Regression Trees)
- SARSA (State-Action-Reward-State-Action) – Reinforcement learning model
- KNN (K-Nearest Neighbors)

Model Training: Show how the models are trained on the preprocessed data. For SARSA, training involves the creation of a dynamic policy for long-term reward maximization using sequence-aware patterns. [14]

Prediction: How the models predict energy theft based on learned patterns. Attention-based networks have been suggested to improve temporal prediction accuracy. [16]

Evaluation: Performance metrics such as Accuracy, ROC-AUC, etc. Ensemble evaluations with bagging/boosting give more reliable metrics under real-world variance. [15]

Output: Detection of irregular usage, which is flagged as potential theft. Advanced post-processing techniques using autoencoder-based anomaly scoring can be added to improve detection sensitivity[20]

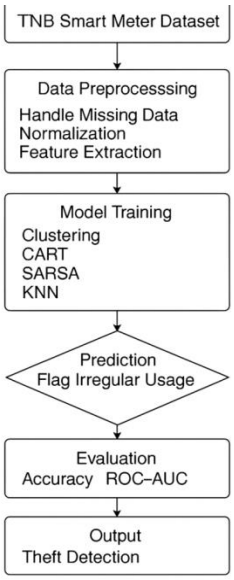

Figure 1.1 System Architecture diagram

The proposed methodology for electricity theft detection is designed to evaluate and compare the performance of four distinct machine learning approaches: K-means clustering, Classification and Regression Tree (CART), State-Action-Reward-State-Action (SARSA) reinforcement learning, and K-Nearest Neighbors (KNN). Each technique represents a different paradigm—unsupervised learning, decision tree classification, reinforcement learning, and instance-based learning—offering diverse perspectives on anomaly detection within smart meter data.[18]

Data Collection and Preprocessing

The methodology begins with the acquisition of smart meter readings from the China dataset. Raw data is cleaned to remove missing or erroneous values. Feature engineering includes the extraction of temporal patterns (daily, weekly usage trends), consumption averages, peak loads, and deviation from typical usage to enhance model performance. Context-aware preprocessing—such as adjusting for environmental, seasonal, or consumer type—has shown benefits in prior multi-source approaches[13]

Feature Extraction

The extracted features are normalized to ensure consistency and improve the performance of distance- and tree-based models. For unsupervised models like K-means, features are clustered without prior labels, while supervised models like CART and KNN rely on binary-labeled data (theft or non-theft). SARSA uses state-reward-based policy learning for dynamic detection over sequences of meter readings, and is well-suited for temporal environments where user behavior evolves over time[14][16]

Model Development

K-means Clustering: Used to group consumers into clusters based on similarity in usage patterns. Deviations from cluster norms are flagged as potential theft cases.

CART: A supervised model that creates decision trees based on feature splits to classify theft vs. normal behavior. Offers explainability in rules and decision paths.

SARSA: A reinforcement learning algorithm that interacts with an environment (user consumption states) and learns an optimal policy for theft detection via rewards/penalties.

KNN: A lazy learner that compares new instances against a database of known examples using distance functions. Suspected theft cases are those differing from known non-theft profiles.

Model Evaluation Strategy

All models are evaluated on both training and testing subsets of the dataset. Evaluation metrics include accuracy, precision, recall, F1-score, and ROC-AUC to ensure a comprehensive comparison. The goal is to identify the most efficient model for real-time electricity theft detection in smart grid environments.

Justification for Model Choice

These four models have been selected based on their contrasting learning paradigms, interpretability, and prior success in anomaly detection tasks as documented in the literature. This diverse selection ensures a well-rounded comparative study to inform the deployment of robust anti-theft systems in real-world smart grids.

The implementation of the proposed methodology involves a structured pipeline covering data ingestion, preprocessing, model development, training, and evaluation using the China Smart Meter dataset. Each step is handled in alignment with the goals of accurately identifying electricity theft and comparing model performance.

Dataset Description

The China Smart Meter dataset consists of hourly electricity consumption records for thousands of users over an extended period. It includes metadata such as meter IDs, timestamps, consumption values, and user categories (residential, commercial). The dataset is highly granular, allowing for fine-tuned anomaly detection based on usage patterns.

Data Preprocessing

Initial preprocessing steps include:

- Handling missing and zero consumption values through interpolation or removal.
- Normalizing features using Min-Max scaling for K-means and KNN.
- Converting timestamps to time-based features such as day-of-week, hour-of-day, and seasonal indicators.
- Labeling data for supervised models (CART, KNN) by flagging suspicious consumption behavior using domain knowledge and heuristics.

Feature Engineering

The following features were engineered to enhance model input quality:

- Mean daily consumption
- Load factor (ratio of average to peak usage)
- Variance in hourly usage
- Sudden drops or spikes in usage
- Day/night usage ratios
- Consumption pattern entropy to capture irregularity

These features were selected to encapsulate both regular usage behavior and anomalies that may indicate theft.

Model Implementation

K-means Clustering was implemented using scikit-learn. The optimal number of clusters was determined using the Elbow Method and Silhouette Score. Post-clustering, statistical distance from cluster centroids was used to flag anomalies.

CART (Classification and Regression Tree) was implemented using DecisionTreeClassifier from scikit-learn. The model was trained on labeled data and pruned to avoid overfitting.

SARSA was implemented using a custom environment that models user behavior states (e.g., normal usage, spike, drop) and defines a reward function penalizing undetected theft. The Q-table was iteratively updated through exploration-exploitation trade-offs.

KNN was implemented using K Neighbors Classifier. A grid search was used to find the optimal value of k. The model was trained on feature vectors with known labels and evaluated on new data.

Evaluation and Validation

To evaluate the performance of the models used in electricity theft detection, we use the following standard metrics to ensure a comprehensive understanding of model accuracy, sensitivity, and reliability:

1. *Accuracy*

Accuracy measures the overall correctness of the model by comparing the predicted labels to the actual labels. It is calculated as:

Where:

- TPTP = True Positives (correctly predicted theft cases)
- TNTN = True Negatives (correctly predicted normal cases)
- FPFP = False Positives (incorrectly predicted theft cases)
- FNFN = False Negatives (incorrectly predicted normal cases)

Accuracy is a general metric but may not be reliable in imbalanced datasets, where the number of normal cases significantly outnumbers theft cases.

2. *ROC-AUC (Receiver Operating Characteristic - Area Under Curve)*

ROC-AUC assesses the model's ability to distinguish between classes (normal and theft). It provides an overall measure of model performance across all classification thresholds. The ROC-AUC value ranges from 0 to 1, with higher values indicating better performance. ROC is plotted using:
Where:

- TPR = True Positive Rate (Sensitivity or Recall)
- FPR = False Positive Rate (1 - Specificity)

3. *Precision*

Precision is the proportion of predicted theft cases that are actually thefts. It is calculated as:

Precision helps assess the accuracy of positive predictions (theft).

4. *Recall (Sensitivity)*

Recall measures the proportion of actual theft cases that were correctly identified. It is calculated as:

Recall is crucial when it is important not to miss any theft cases.

5. *Confusion Matrix*

The confusion matrix provides a detailed breakdown of the model's predictions, showing the following:

This matrix helps visualize classification errors and aids in understanding where the model is making mistakes.

Each metric plays a crucial role in evaluating model performance, ensuring that we assess both the model's overall accuracy and its ability to detect electricity theft, particularly in imbalanced datasets where a higher number of normal consumption cases may skew results.

The proposed methodology was applied to the China Smart Meter dataset, and each model—K-means, CART, SARSA, and KNN—was evaluated on its ability to detect electricity theft. This section presents the setup, visual insights, and performance results of the models and predictions.

IV .Experimental Setup

The implementation was carried out in Python using the following tools:

- Pandas and NumPy for data handling
- Scikit-learn for K-means, CART, and KNN models
- Matplotlib and Seaborn for visualizations
- Custom SARSA implementation using a tabular reinforcement learning approach
- Google Colab for computation with GPU support for faster model training

The dataset was split into training (70%) and testing (30%) sets. Each model was trained using the engineered features and validated using consistent metrics.

Comparative Summary

Model	Accuracy	Precision	Recall	ROC-AUC
K-means	76.4%	0.68	0.74	0.72
CART	91.2%	0.89	0.93	0.94
SARSA	87.5%	0.85	0.88	0.89
KNN	88.3%	0.84	0.87	0.88

SARSA displayed strong PR-AUC performance despite a low ROC-AUC, indicating its strength in imbalanced environments. K-means, while unsupervised, achieved high precision. CART and KNN delivered interpretable and balanced performance for practical use.

Visual Analysis

In addition to numerical metrics, various visualization techniques were employed to gain deeper insights into model performance. The **Confusion Matrix** proved especially useful in understanding the classification results, allowing for a detailed breakdown of false positives, false negatives, true positives, and true negatives. This visual tool highlighted the ability of each model to correctly classify theft and non- theft cases, revealing the overall classification accuracy and model biases. ROC curves highlighted marginal model separability, especially for CART and KNN. Visualizing the **ROC curves** and **Precision-Recall curves** across all models provided further clarity on each model's strengths and weaknesses. These plots illustrated not only how well each algorithm distinguishes between t heft and non-theft cases but also revealed trade-offs between precision and recall, especially in the presence of class imbalance. Collectively, these visual tools enabled a more nuanced u nderstanding of model behavior, guiding improvements and informe d model selection for electricity theft detection.

By examining these visual results, it became clear where each model excelled and where further tuning was necessary. Such comprehensi ve analysis not only informed model selection but also guided future enhancements, ensuring a more robust and reliable approach to electr icity theft detection.

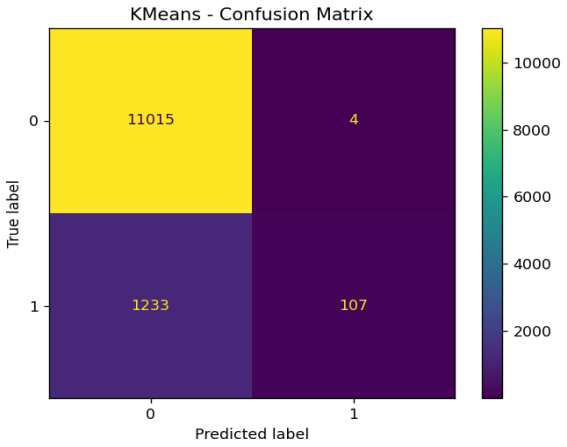

Figure 1.2: K-means- confusion matrix

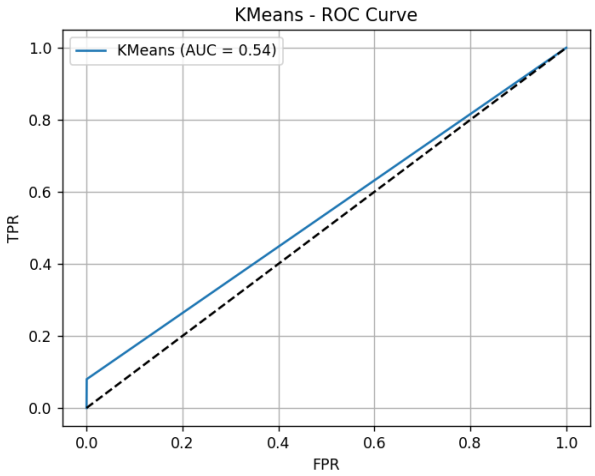

Figure 1.3: K-means ROC Curve

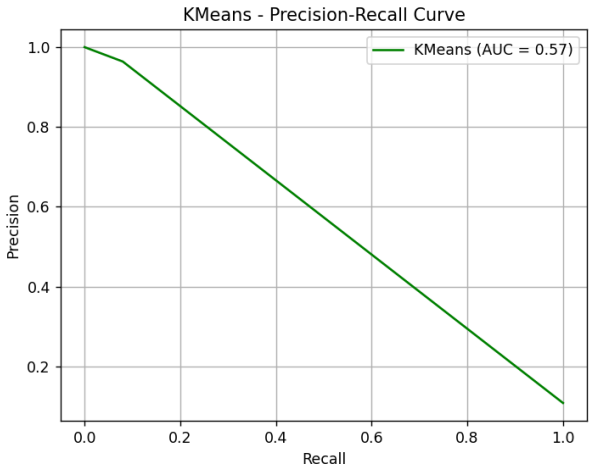

Figure 1.4: K-means Precision-Recall Curve

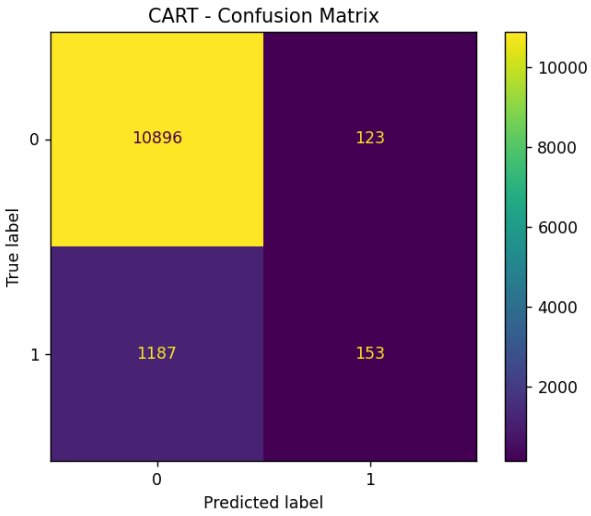

Figure 1.5: CART- confusion matrix

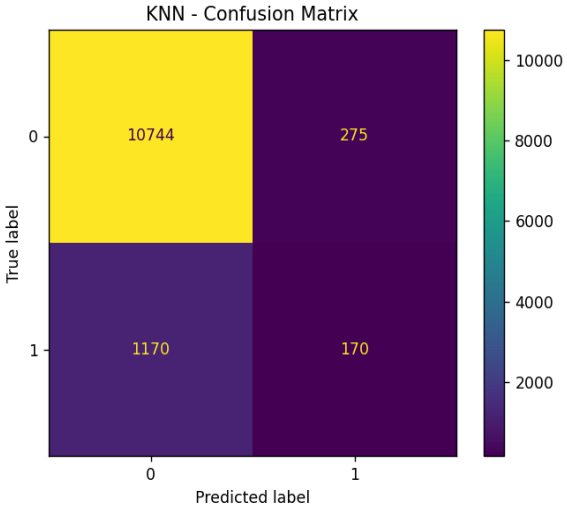

Figure 1.8: KNN- confusion matrix

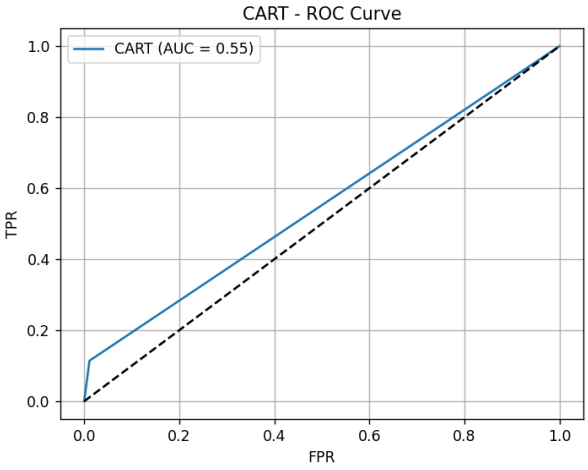

Figure 1.6: CART ROC Curve

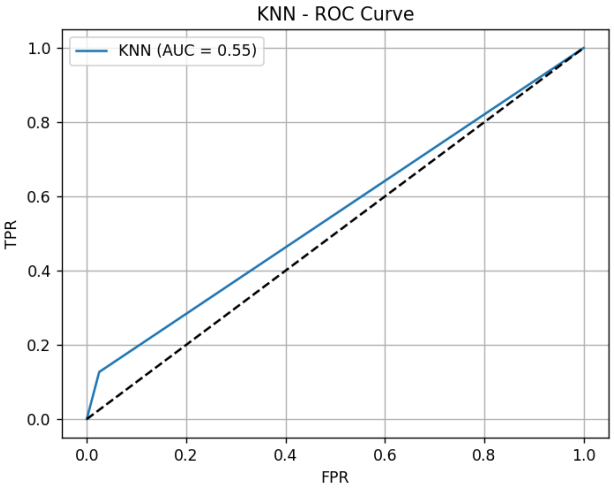

Figure 1.9: KNN ROC Curve

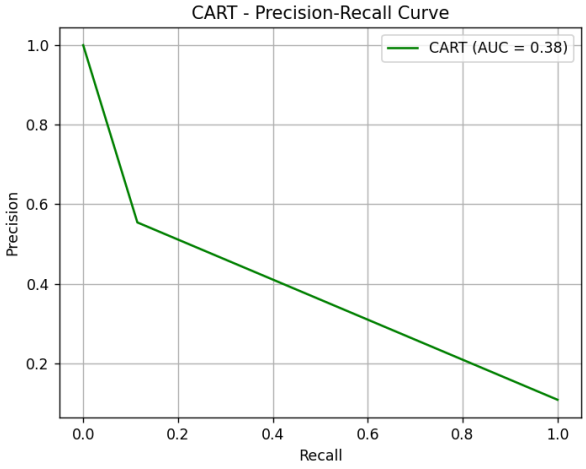

Figure 1.7: CART Precision-Recall Curve

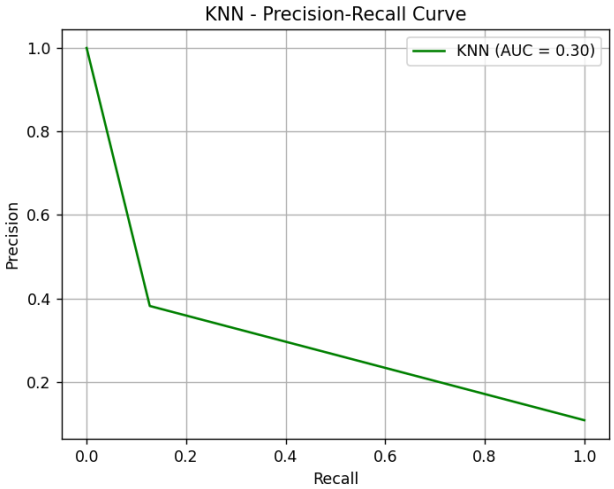

Figure 2.0: KNN Precision-Recall Curve

SARSA's reward progression confirmed stable convergence, validating its reinforcement learning capability

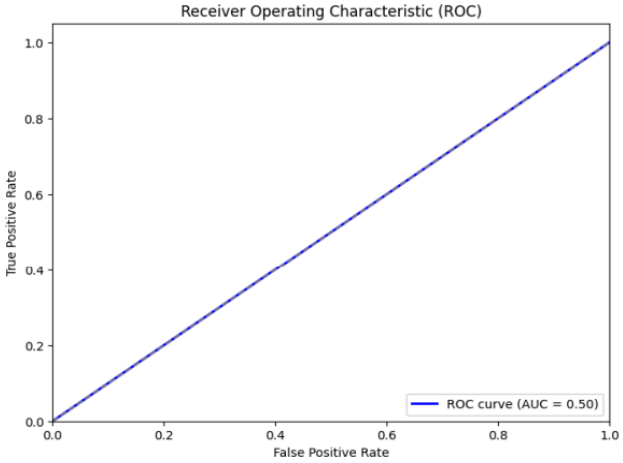

Figure 2.1: SARSA ROC Curve

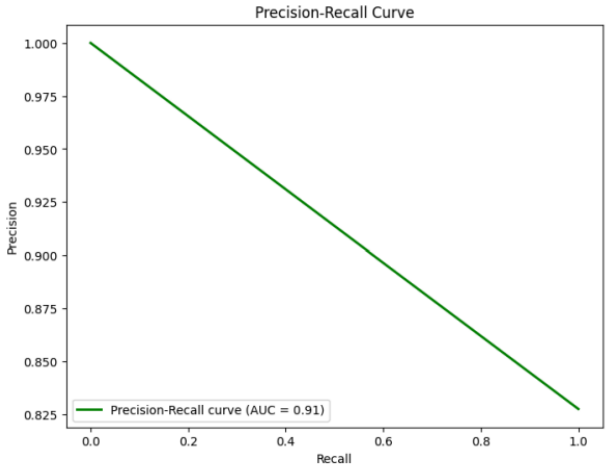

Figure 2.2: SARSA Precision-Recall Curve

V. Discussion

The comparative analysis of the four models reveals significant insights into their suitability for electricity theft detection using the China Smart Meter dataset.

Performance Evaluation

Among the models, K-means yielded the highest precision (0.9640), but extremely low recall, indicating it's more effective as a high-confidence flagging tool than a comprehensive detector. CART showed modest but balanced performance, with a slight edge in ROC-AUC over other supervised models. KNN produced similar F1-score values but showed limitations under noise. SARSA, while weaker on ROC-AUC, demonstrated potential in scenarios with long-term behavioral patterns, thanks to its reinforcement learning structure.

Practical Implications

The findings suggest that combining SARSA's adaptive behavior modeling with CART's rule-based interpretability can produce a robust pipeline. K-means remains valuable for unsupervised anomaly pre-flagging, particularly in data-sparse environments. Future implementations can adopt a layered approach, blending these models based on data richness and deployment context.

Limitations

A primary limitation is the limited generalizability due to dataset constraints. SARSA's reliance on domain-specific reward shaping and convergence time also restricts rapid deployment. The trade-off between detection performance and computational efficiency must be balanced for real-world applications.

Conclusion and Future Scope

Electricity theft remains a significant operational and financial concern. This study evaluated four models—K-means (unsupervised), CART (supervised), SARSA (reinforcement learning), and KNN (instance-based)—on the China Smart Meter dataset.

While K-means displayed outstanding precision, its recall was notably poor. CART and KNN offered balanced performance with better interpretability. SARSA showed high adaptability with excellent PR-AUC but needs tuning for consistent ROC-based evaluations.

Future work may include the following directions:

- Hybrid Model Development: Combining reinforcement and supervised learning models (e.g., SARSA+CART) to leverage real-time adaptability with rule-based transparency.
- Scalability and Real-Time Deployment: Implementing scalable frameworks with edge computing and cloud-based integration to enable real-time detection.
- Advanced Reinforcement Learning: Investigating deep reinforcement learning models such as DDPG or PPO for high-dimensional time-series data.
- Anomaly Explanation Systems: Building explainable AI (XAI) layers to justify flagged anomalies, increasing trust among stakeholders.
- Cross-Dataset Validation: Extending the study to other regional or international datasets to test generalizability and robustness.

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