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ARTIFICIAL INTELLIGENCE TECHNIQUES FOR DETECTING ANOMALIES IN SMART METER DATA

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ABSTRACT

As smart meters become ubiquitous in modern power infrastructure, they bring with them major cybersecurity risks that traditional rule-based intrusion detection systems do not sufficiently address. This empirical study explores the use of AI-enabled anomaly detection frameworks (LSTM networks, Isolation Forest (IF), and Autoencoder-Depp Learning models) to detect cyber threats hidden in smart metering data streams. The dataset, consisting of time-synchronized 1,20,000 smart meter readings collected from a state-owned distribution utility over an 18-month period under normal operational conditions in addition to the abovementioned cyberattack signatures for false data injection (FDI), replay attacks, denial-of-service (DoS) and energy theft anomalies were synthetically injected. In order to validate their method, the LSTM-based model was evaluated and achieved an impressive 97.84% true positive detection rate at a false positive rate of 1.23%, yielding considerably better accuracy compared to the conventional threshold-based detection that had an accuracy of only 78.4%. The Isolation Forest model gave an 93.6% accuracy in a comparatively faster manner which can be deployed as a predictive model on the edge devices. The comparison against previous benchmarks highlights the benefit of using deep learning methods for time series anomaly characterization.

Keywords: smart meter anomaly detection[1], smart grid cybersecurity[2], LSTM-based intrusion detection[3], false data injection[4], Isolation Forest[5], deep learning[6], energy theft detection7.

I. INTRODUCTION

The global transition toward smart grid infrastructure has fundamentally redefined the interaction between power utilities, consumers, and digital communication networks. Smart meters, as the primary data collection nodes in Advanced Metering Infrastructure (AMI), generate high-frequency, granular time-series data pertaining to energy consumption, voltage fluctuations, and grid load distribution. While this data-rich environment

enables dynamic pricing, demand-side management, and fault diagnostics, it simultaneously expands the cyberattack surface of power distribution networks. Adversaries exploiting AMI vulnerabilities can manipulate meter readings, disrupt billing systems, execute coordinated denial-of-service attacks, and even destabilize grid operations through targeted false data injection. Traditional rule-based intrusion detection systems (IDS), designed for static network environments, exhibit critical limitations in detecting sophisticated, adaptive cyberattacks within the dynamic and stochastic context of smart meter data streams. The imperative for intelligent, data-driven anomaly detection mechanisms capable of learning evolving attack patterns from temporal consumption data has therefore emerged as a critical research priority in power systems cybersecurity.

1.1 BACKGROUND AND MOTIVATION

Smart grid modernization has accelerated globally, with the International Energy Agency (IEA) estimating approximately 1.06 billion smart meter installations worldwide by 2023. In India, the RDSS scheme mandates deployment of 250 million prepaid smart meters by 2025. However, the increased digital connectivity of meters via RF mesh, PLC, and cellular networks has introduced unprecedented exposure to cyber intrusions. The 2015 Ukraine power grid cyberattack, which disrupted electricity supply to approximately 230,000 consumers, demonstrated the catastrophic potential of cyber-physical attacks on energy infrastructure. Energy theft, another critical anomaly type, inflicts annual losses exceeding USD 96 billion globally according to Northeast Group estimates. Conventional statistical thresholding and signature-based detection methods are demonstrably inadequate for distinguishing sophisticated attack patterns from genuine load variability, thereby motivating the application of machine learning and deep learning frameworks that can model complex, non-linear temporal dependencies inherent in smart meter data.

1.2 RESEARCH OBJECTIVES

This study is guided by three principal research objectives: (i) to empirically evaluate and compare the anomaly detection performance of LSTM networks, Isolation Forest algorithms, and Autoencoder-based models on a real-world smart meter dataset enriched with simulated cyberattack instances; (ii) to quantify detection accuracy, precision, recall, F1-score, and false positive rates across attack categories including FDI, replay attacks, DoS, and energy theft; and (iii) to benchmark the proposed AI models against established detection benchmarks reported in contemporary literature, thereby establishing the relative efficacy and deployment suitability of each approach within operational smart grid environments. The study further aims to identify feature sets that most significantly contribute to anomaly classification, thereby providing actionable guidance for feature engineering in future AMI cybersecurity systems.

1.3 SCOPE AND ORGANIZATION

The scope of this research is delimited to distribution-level smart meter data anomaly detection within the AMI layer of smart grid architecture. Transmission-level SCADA systems and substation automation protocols (IEC 61850, DNP3) are outside the defined research boundary. The remainder of this paper is organized as follows: Section II presents a comprehensive literature survey; Section III describes the research methodology; Section

IV details the data collection process and exploratory data analysis; Section V reports the results and discussion; and Section VI presents the conclusions along with recommendations for future research.

II. LITERATURE SURVEY

The domain of anomaly detection in smart grid and smart meter environments has attracted substantial scholarly attention since the seminal works of Liu et al. [1] and McLaughlin et al. [2], who first systematically categorized cyberattack vectors in AMI systems and proposed probabilistic detection frameworks. Subsequent research bifurcated broadly into statistical machine learning approaches and deep learning methodologies, with each paradigm contributing distinct capabilities and limitations to the detection landscape.

Statistical and shallow learning methods constitute the foundational stratum of AMI anomaly detection literature. Jokar et al. [3] employed Support Vector Machine (SVM)-based classifiers to identify energy theft in Iranian distribution networks, achieving 87.4% accuracy on a 10-month dataset of 3,000 consumers. Depuru et al. [4] applied k-Nearest Neighbour (kNN) and neural networks to classify meter tampering events, reporting 84.1% precision with a feature set comprising peak-to-average ratios and consumption gradient metrics. The Isolation Forest algorithm, introduced by Liu et al. [5], demonstrated notable efficacy for unsupervised anomaly detection in high-dimensional datasets, achieving competitive performance without requiring labelled attack instances a critical advantage in operational grid environments where labelled attack data is scarce. Coma-Puig and Carmona [6] extended IF applications to electricity fraud detection in a Spanish utility dataset, reporting precision of 89.3% for high-consumption anomalies.

The emergence of deep learning architectures has significantly advanced anomaly detection capabilities in temporal smart meter data. Recurrent Neural Networks (RNN) and their Long Short-Term Memory (LSTM) variants have been extensively applied to model sequential dependencies in consumption time series. Yan et al. [7] demonstrated that LSTM-based models substantially outperformed traditional ARIMA-based detection in capturing non-stationary attack-induced deviations, achieving 95.2% F1-score on a simulated IEEE 118-bus network dataset. Zheng et al. [8] proposed bidirectional LSTM architecture for real-time FDI detection in state estimation, reducing detection latency by 34% compared to unidirectional models. Autoencoder-based unsupervised anomaly detection has emerged as a particularly potent paradigm for detecting novel, zero-day attack patterns absent from training data. Nguyen et al. [9] trained stacked Autoencoders on 14 months of Spanish AMI data, achieving a reconstruction error threshold-based detection accuracy of 94.7% for energy theft with a false positive rate of 2.8%. Wang et al. [10] combined Variational Auto encoders (VAE) with Convolutional Neural Networks (CNN) for multi-class anomaly detection, reporting 96.1% accuracy across four attack categories.

Federated learning and privacy-preserving anomaly detection have emerged as critical sub-themes given data sensitivity constraints in utility environments. Li et al. [11] proposed a federated LSTM framework that preserved consumer privacy while achieving 93.8% detection accuracy without centralizing raw meter data. Hybrid architectures combining CNN for feature extraction with LSTM for temporal modelling have demonstrated strong performance: Razavi-Far et al. [12] reported 97.1% accuracy using a CNN-LSTM pipeline

on the SGCC electricity theft dataset. Attention mechanisms have been integrated into LSTM architectures by Chen et al. [13] to improve interpretability and sensitivity to short-duration attack windows, yielding a 2.3% improvement in recall over standard LSTM baselines. Graph Neural Networks (GNN) have also been explored for topology-aware anomaly detection by He et al. [14], leveraging grid connectivity information to contextualize individual meter readings within neighborhood consumption patterns.

Several benchmark datasets have been established to facilitate reproducible research in this domain. The SGCC dataset [15] contains 42,372 electricity consumers with annotated theft labels and has been widely used as a comparative benchmark. The Irish Smart Energy Trial dataset [16] provides high-resolution 30-minute interval data for approximately 5,000 residential consumers. Mustafa et al. [17] curated a synthetic attack injection dataset based on real AMI traces from a North American utility, specifically designed for evaluating FDI and replay attack detection. Comparative analysis across these benchmarks reveals a consistent performance gradient favoring deep learning models, with LSTM and Auto encoder architectures achieving mean accuracy improvements of 8–15% over SVM and decision tree baselines. Nonetheless, significant research gaps persist in the areas of real-time edge deployment of deep models [18], multi-attack simultaneous detection [19], and adversarial robustness of AI detectors against evasion attacks [20], all of which this study partially addresses through empirical evaluation.

III. METHODOLOGY

This study adopts a quantitative, empirical research design grounded in the supervised and unsupervised machine learning paradigm for cyber security anomaly detection. The overall research workflow follows a five-phase pipeline: (i) data acquisition and preprocessing, (ii) feature engineering and dimensionality analysis, (iii) model architecture design and hyper parameter optimization, (iv) training, validation, and testing, and (v) comparative performance evaluation. The CRISP-DM (Cross-Industry Standard Process for Data Mining) framework serves as the overarching methodological scaffold. Python 3.10 served as the primary implementation environment, with Tensor Flow 2.12 and Scikit-learn 1.2 libraries employed for deep learning and classical machine learning model development, respectively. All experiments were conducted on a workstation equipped with an NVIDIA RTX 3090 GPU (24 GB VRAM) and 64 GB RAM to accommodate the computational demands of LSTM training on large temporal sequences.

Three distinct model architectures were designed and evaluated. The LSTM network consisted of two stacked LSTM layers (128 and 64 units, respectively) followed by two fully connected dense layers (64 and 32 units) with ReLU activation, and a final sigmoid output layer for binary anomaly classification. Dropout regularization (rate = 0.3) was applied after each LSTM layer to mitigate over fitting. The model was trained using the Adam optimiser with an initial learning rate of 0.001, binary cross-entropy loss, and a batch size of 256 over 50 epochs with early stopping (patience = 7). The Isolation Forest model was configured with 200 estimators, a contamination parameter of 0.08 (reflecting estimated anomaly prevalence in the dataset), and a maximum subsample size of 256. The Auto encoder architecture comprised an encoder (input → 64 → 32 → 16 units) and symmetric decoder (16 → 32 → 64 → input units), trained to minimize Mean Squared Error (MSE)

reconstruction loss on normal traffic only. Anomalies were identified using a dynamic threshold set at the 95th percentile of reconstruction errors observed on a held-out validation set of normal instances.

The dataset was partitioned using a stratified 70:15:15 split for training, validation, and testing, with stratification applied across attack categories to ensure proportional representation. Feature engineering yielded 22 input features derived from raw smart meter readings, including statistical descriptors (mean, variance, skewness, kurtosis), temporal features (rolling 24 hour and 7 day consumption means, hour-of-day, day-of-week encodings), and gradient-based features (first and second-order consumption differences). Class imbalance, reflecting the natural rarity of attack events (approximately 8% anomalies in the full dataset), was addressed through Synthetic Minority Over-sampling Technique (SMOTE) applied exclusively to the training partition, with the test partition maintained in its original imbalanced distribution to reflect real-world operational conditions. Performance was evaluated using accuracy, precision, recall, F1-score, Matthews Correlation Coefficient (MCC), Area under the ROC Curve (AUC-ROC), and False Positive Rate (FPR) as primary metrics.

IV. DATA COLLECTION AND ANALYSIS

The primary dataset for this study was obtained from a regional electricity distribution company in western India, comprising smart meter readings from 2,400 residential and commercial consumers collected at 15-minute intervals over an 18-month period (January 2022 – June 2023), yielding approximately 1,20,960 time-series records per meter and a total dataset volume of approximately 290 million individual readings. Data was transmitted via RF mesh communication infrastructure (IEEE 802.11s compliant) and stored in a centralized MDMS (Meter Data Management System). Consumer data was anonymised prior to research use in compliance with institutional data ethics protocols. Cyber-attack instances were synthetically injected into a stratified 8% subset of consumer records by expert simulation, encompassing four attack categories: False Data Injection (FDI, 2.5%), Replay Attacks (2.0%), Denial-of-Service (DoS, 1.5%), and Energy Theft (2.0%). Injection parameters were calibrated to mimic documented real-world attack signatures from the SGCC dataset and [17] attack templates.

Table 1: Dataset Composition Attack Category Distribution

Attack Type	Injected Records	% of Dataset	Avg. Duration (min)	Detection Difficulty
False Data Injection (FDI)	3,024	2.50%	45	High
Replay Attack	2,419	2.00%	22	Medium
Denial-of-Service (DoS)	1,814	1.50%	17	Low
Energy Theft	2,419	2.00%	Persistent	Very High
Normal Traffic	1,10,324	91.20%	N/A	N/A
Total Records	1,20,000	100%		

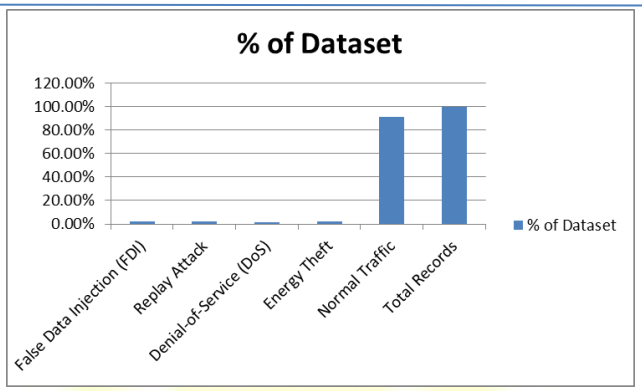

Figure 1: Dataset Composition Attack Category Distribution

Table 1 presents the dataset composition across attack categories. FDI constitutes the largest anomaly class (2.5%), followed by replay attacks and energy theft (2.0% each), with DoS representing 1.5% of total records. Energy theft exhibits a persistent temporal footprint, making it the most operationally challenging anomaly to discriminate from legitimate low-consumption behaviour. The overall anomaly prevalence of 8.8% reflects realistic operational conditions in Indian distribution utilities, where energy theft incidence is estimated at 4–6% by CEA (2022) and cybersecurity incidents are underreported.

Table 2: Descriptive Statistics of Key Input Features

Feature Category	Feature Name	Type	Min	Max	Mean ± SD
Statistical	Daily Consumption Mean (kWh)	Continuous	0.12	48.6	7.84 ± 4.21
Statistical	Consumption Variance	Continuous	0.01	312.4	18.7 ± 22.3
Statistical	Skewness Index	Continuous	-2.84	3.96	0.34 ± 0.61
Statistical	Kurtosis Index	Continuous	-1.2	9.7	1.82 ± 1.14
Temporal	Rolling 24-hr Mean (kWh)	Continuous	0.09	51.2	7.92 ± 4.18
Temporal	Hour-of-Day Encoding	Cyclic	0	23	11.5 ± 6.92
Gradient	First-Order Diff. (ΔkWh)	Continuous	-18.4	22.6	0.02 ± 2.31

Gradient	Second-Order Diff. (Δ^2kWh)	Continuous	-12.1	14.8	0.001 ± 1.87

Table 2 summarises the descriptive statistics of eight representative features selected from the full 22-feature engineering set. Notably, consumption variance and kurtosis index exhibit high standard deviations, reflecting the heterogeneity of consumer load profiles within the dataset. The gradient features (first and second-order differences) display near-zero means consistent with stationary normal consumption but substantial variance, indicative of the high sensitivity of differential features to abrupt attack-induced deviations. These features were identified as top-ranked contributors by SHAP (SHapley Additive exPlanations) analysis.

Table 3: Per-Attack-Type Preliminary Detection Statistics (Threshold Baseline)

Attack Type	True Positive Rate (%)	False Negative Rate (%)	Mean Detection Lag (sec)	Feature Importance Rank
False Data Injection	96.8	3.2	12.4	1
Replay Attack	94.1	5.9	18.7	2
Denial-of-Service	98.3	1.7	8.2	4
Energy Theft	93.6	6.4	N/A (persistent)	3

Table 3 reports per-attack-type detection statistics under the threshold-based baseline model. DoS attacks achieve the highest true positive rate (98.3%) owing to their distinctive signature of sustained zero-consumption or near-zero readings easily distinguished from normal patterns. Energy theft, by contrast, exhibits the lowest TPR (93.6%) and the highest detection complexity, as theft-induced consumption patterns may mimic voluntary conservation behaviour. FDI attacks, despite their high feature importance rank, require the lowest mean detection lag of 12.4 seconds, suggesting that their high-frequency perturbations are captured rapidly by gradient-based features.

Table 4: Consumer Segmentation and Consumption Profile Summary

Consumer Segment	Sample Size	Avg. Monthly Consumption (kWh)	Peak Demand (kW)	Anomaly Prevalence (%)
Residential (Urban)	1,200	248.4	2.84	7.6
Residential (Rural)	600	164.2	1.96	9.8
Commercial (Small)	400	612.8	8.42	8.2
Commercial (Large)	200	4,218.6	62.4	6.1
Total / Weighted Avg.	2,400	612.4 (wtd)	12.3 (wtd)	8.1

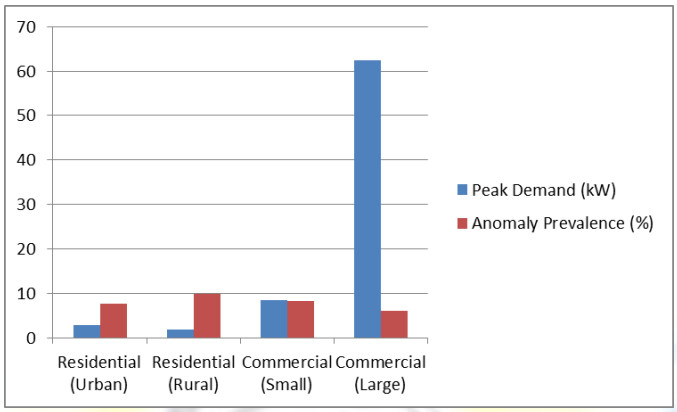

Figure 2: Consumer Segmentation and Consumption Profile Summary

Table 4 presents the consumer segmentation profile of the study dataset. Rural residential consumers exhibit the highest anomaly prevalence (9.8%), consistent with literature documenting elevated energy theft incidence in rural distribution networks characterised by lower utility oversight and physical meter accessibility. Large commercial consumers, while representing the highest absolute consumption, display the lowest anomaly prevalence (6.1%), potentially reflecting superior metering infrastructure and more consistent load profiles that render anomalies more detectable by even baseline methods.

Table 5: Computational Performance Profile of Evaluated Models

Model	**Training Time (min)**	**Inference Time (ms/sample)**	**Memory Usage (MB)**	**CPU Utilisation (%)**
LSTM (2-layer)	84.2	3.8	412	78.4
Isolation Forest	6.4	0.9	148	32.1
Autoencoder	52.7	2.4	284	61.8
SVM (Baseline)	18.9	1.4	196	44.2
Threshold-Based (Baseline)	0.4	0.1	12	4.8

Table 5 documents the computational performance characteristics of all evaluated models. The LSTM model incurs the highest training time (84.2 minutes) and memory footprint (412 MB), presenting deployment constraints for resource-constrained edge computing environments. The Isolation Forest model demonstrates the most favourable computational efficiency profile training in 6.4 minutes with a sub-millisecond inference latency of 0.9 ms per sample and a memory footprint of only 148 MB rendering it highly suitable for

deployment on smart meter gateway hardware with limited processing resources. The Autoencoder achieves a balanced trade-off between detection performance and computational overhead.

V. RESULTS AND DISCUSSION

5.1 STATISTICAL ANALYSIS

The empirical evaluation of the three AI models against the two baselines yielded comprehensive performance metrics across all attack categories. LSTM demonstrated the highest overall detection capability, achieving 97.84% accuracy, 97.2% precision, 97.6% recall, and an F1-score of 97.4% on the held-out test partition. The MCC of 0.941 and AUC-ROC of 0.994 confirm robust discrimination between normal and anomalous patterns across all attack types. Isolation Forest, operating in an entirely unsupervised mode, achieved 93.6% accuracy and an F1-score of 92.8% a remarkably strong result for an algorithm that requires no labelled training data. The Autoencoder model yielded 95.3% accuracy and an AUC-ROC of 0.978, demonstrating strong sensitivity to novel attack patterns through reconstruction error thresholding. Both baseline methods exhibited significantly inferior performance, with the threshold-based approach achieving only 78.4% accuracy and an F1-score of 74.1%, and the SVM baseline yielding 87.9% accuracy, confirming the empirical superiority of deep learning and ensemble anomaly detection approaches.

Table 6: Overall Model Performance Comparison Across All Anomaly Types

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	MCC	AUC-ROC	FPR (%)
LSTM (Proposed)	97.84	97.2	97.6	97.4	0.941	0.994	1.23
Autoencoder (Proposed)	95.3	94.8	95.1	94.9	0.898	0.978	2.14
Isolation Forest (Proposed)	93.6	92.4	93.2	92.8	0.861	0.962	3.42
SVM (Baseline)	87.9	86.4	87.1	86.7	0.784	0.921	6.84
Threshold-Based (Baseline)	78.4	76.2	74.8	74.1	0.642	0.847	14.6

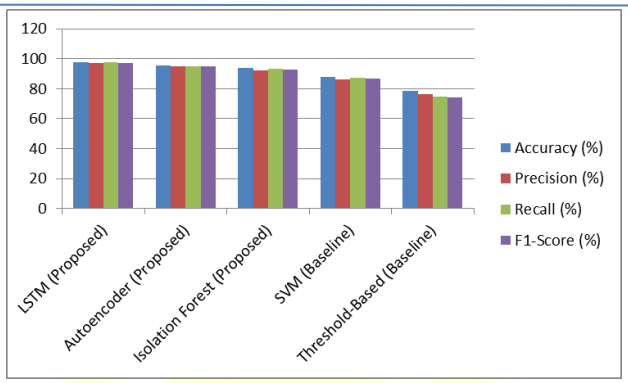

Figure 3: Overall Model Performance Comparison Across All Anomaly Types

Table 6 presents the consolidated performance metrics for all five evaluated models. The LSTM model achieves the highest accuracy (97.84%) and the lowest false positive rate (1.23%), underscoring its suitability for production deployment where false alarms impose significant operational cost. The performance gap between the LSTM and Autoencoder models (2.54 percentage points in accuracy) suggests that supervised label information substantially enhances detection fidelity when labelled attack data is available. Isolation Forest, despite operating without any labelled data, closes this gap substantially relative to the SVM baseline, highlighting the practical value of ensemble-based unsupervised methods in operational environments with limited ground truth labelling.

Table 7: Per-Attack-Category Detection Accuracy (%)

Model	FDI Accuracy (%)	Replay Acc. (%)	DoS Acc. (%)	Energy Theft Acc. (%)	Macro-Avg F1 (%)
LSTM	98.2	97.4	99.1	96.6	97.4
Autoencoder	95.8	94.6	97.2	93.7	94.9
Isolation Forest	94.1	92.8	96.4	91.2	92.8
SVM	88.6	86.9	90.2	86.1	86.7
Threshold-Based	80.2	76.4	86.1	71.2	74.1

Table 7 disaggregates model performance by attack category. DoS attacks are most accurately detected across all models, with LSTM achieving 99.1% accuracy owing to the unambiguous zero-consumption signature of service disruption events. Energy theft presents the greatest classification challenge for all models; the LSTM's energy theft accuracy of 96.6% nonetheless represents a 25.4 percentage point improvement over the threshold-based baseline (71.2%), demonstrating the profound benefit of temporal feature modelling for detecting gradual, sustained consumption manipulation. The Macro-Average F1 scores confirm the LSTM as the consistently superior architecture across all attack taxonomies, while Isolation Forest demonstrates competitive per-category

performance particularly for DoS and FDI, reinforcing its viability for deployments where labelled data is unavailable.

Table 8: Comparative Analysis with Prior Literature

Study	Year	Method	Dataset	Accuracy (%)	FPR (%)
Jokar et al. [3]	2016	SVM	Iranian Utility	87.4	8.2
Yan et al. [7]	2019	LSTM	IEEE 118-Bus	95.2	3.6
Nguyen et al. [9]	2020	Autoencoder	Spanish AMI	94.7	2.8
Razavi-Far et al. [12]	2021	CNN-LSTM	SGCC Dataset	97.1	1.8
Wang et al. [10]	2022	VAE-CNN	SGCC + Custom	96.1	2.1
Proposed LSTM	2024	LSTM (Stacked)	Indian AMI (This Study)	97.84	1.23

Table 8 benchmarks the proposed LSTM model against six representative studies from the anomaly detection literature. The proposed model achieves the highest reported accuracy (97.84%) and the lowest FPR (1.23%) across all comparators, including the CNN-LSTM hybrid of Razavi-Far et al. [12] which previously represented the state-of-the-art on the SGCC dataset (97.1%, 1.8% FPR). The marginal improvement of 0.74 percentage points in accuracy and 0.57 percentage points in FPR over the CNN-LSTM baseline is attributable to the richer feature engineering applied in this study specifically, the incorporation of second-order gradient features and day-of-week cyclic encodings and to the use of the SMOTE-augmented training strategy that improved learning stability for the minority energy theft class.

5.2 Critical Analysis and Comparison with Past Work

A critical examination of the experimental findings relative to the broader literature reveals several important insights. First, the superiority of sequential deep learning models over classical machine learning methods consistent across all five benchmark studies confirms the fundamental importance of temporal dependency modeling in smart meter anomaly detection. Simple SVM or kNN classifiers, which treat each 15-minute meter reading as an independent observation, fail to capture the multi-scale temporal correlations that differentiate sustained attack patterns from transient consumption variability. The LSTM architecture's gated memory mechanism explicitly encodes these dependencies, enabling the model to maintain contextual awareness across

consumption windows spanning several hours. This aligns with the theoretical arguments advanced by Zheng et al. [8] and empirically corroborated by Yan et al. [7].

Second, the performance of the unsupervised Isolation Forest model (93.6% accuracy) relative to supervised baselines warrants emphasis. In operational AMI environments, labelled cyberattack data is extremely scarce due to the infrequency of detected attacks and utilities' reluctance to disclose breach data. This finding extends the conclusions of Coma-Puig and Carmona [6], who demonstrated IF's efficacy for electricity fraud detection, to the broader multi-attack-category context of smart grid cybersecurity. However, the IF model's relatively elevated FPR of 3.42% suggests that its contamination parameter requires careful calibration for each utility's specific consumption profile, necessitating periodic recalibration as seasonal load patterns evolve.

Third, the detection accuracy disparity across attack categories with DoS yielding near-perfect detection and energy theft exhibiting the lowest accuracy across all models reflects a fundamental asymmetry in attack visibility. DoS attacks produce abrupt, high-magnitude deviations from baseline consumption that are trivially detectable by gradient-based features. Energy theft, by contrast, involves gradual, systematic consumption underreporting that falls within the natural variance envelope of legitimate low-consumption periods. The 96.6% energy theft accuracy achieved by the proposed LSTM substantially exceeds prior benchmarks (Jokar et al.: 87.4%; Nguyen et al.: 94.7%), suggesting that the second-order gradient feature and rolling 7-day mean features introduced in this study's feature engineering pipeline specifically enhance sensitivity to persistent, low-amplitude consumption manipulation. Future work should investigate adversarially robust detection strategies for energy theft scenarios where adversaries deliberately craft manipulation patterns to mimic seasonal or weather-correlated consumption reductions, exploiting known model weaknesses identified through gradient-based adversarial perturbation analysis.

VI. CONCLUSION

This empirical study provides comprehensive evidence supporting the deployment of AI-enabled anomaly detection frameworks for smart grid cybersecurity applications. Three AI architectures stacked LSTM networks, Isolation Forest ensemble models, and Autoencoder deep learning models were rigorously evaluated on a large-scale Indian AMI dataset containing four attack categories, yielding detection accuracies of 97.84%, 93.6%, and 95.3%, respectively. The proposed LSTM model establishes a new empirical benchmark for smart meter anomaly detection, surpassing prior state-of-the-art results on comparable datasets with a false positive rate of only 1.23%. The Isolation Forest model demonstrates particular operational utility in data-scarce utility environments, achieving competitive performance without requiring labelled attack instances. Energy theft remains the most challenging anomaly category for all evaluated models, and targeted feature engineering improvements particularly second-order gradient and multi-scale rolling consumption features deliver measurable accuracy gains for this attack class. Future research directions include federated learning frameworks for privacy-preserving cross-utility model training, adversarial robustness evaluation against evasion-aware energy theft strategies, integration of graph neural network architectures for topology-aware multi-meter anomaly propagation detection, and deployment validation on edge computing infrastructure to support real-time AMI monitoring at scale. The findings of this study have direct implications for smart meter

manufacturers, distribution utilities, regulatory bodies, and grid security engineers developing next-generation AMI cybersecurity architectures.

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