LW-EdgeNet: Lightweight Edge-Based Deep Learning for Smart Meter Energy Theft Detection Using the SGCC Dataset

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Abstract

Energy theft constitutes a growing operational and financial threat to utilities deploying IoT-enabled smart meter networks, with annual global losses estimated to exceed USD 96 billion. Existing deep learning detection models achieve high accuracy but impose computational demands that render them unsuitable for resource-constrained edge hardware. This paper proposes LW-EdgeNet, a lightweight deep learning architecture built around depthwise separable convolutions, bottleneck residual blocks, and squeeze-and-excitation channel attention, designed specifically for real-time inference on embedded edge nodes. Evaluated on the State Grid Corporation of China (SGCC) Electricity Theft Detection dataset, LW-EdgeNet achieves 98.1% detection accuracy, 94.7% precision, 93.4% recall, a 94.1% F1-score, and an AUC-ROC of 0.9923, outperforming five competitive baseline models. Statistical significance testing confirms that LW-EdgeNet's improvements over the best baseline (CNN-LSTM) are significant at $p < 0.01$ using the paired Wilcoxon signed-rank test. SHAP-based explainability analysis identifies the most influential temporal regions within the 30-day consumption window. Deployed on a Raspberry Pi 4B edge node, the model completes inference in 4.2 ms, occupies just 0.38 MB of quantized memory, and draws 1.9 W average power. These results establish LW-EdgeNet as a compelling, interpretable, and statistically validated candidate for practical edge deployment in smart meter networks.

Keywords: energy theft detection; smart meter; edge computing; lightweight deep learning; IoT; SGCC dataset; depthwise separable convolution; squeeze-and-excitation attention; explainability.

1. Introduction

The global deployment of advanced metering infrastructure (AMI) has transformed conventional power grids into data-intensive IoT-enabled ecosystems. Smart meters now continuously record electricity consumption at 15-minute intervals, enabling demand-side management, real-time fault detection, and dynamic tariff adjustment. However, this same connectivity exposes the grid to sophisticated non-technical losses, commonly termed energy theft, which generate estimated global annual losses exceeding USD 96 billion (Smith et al., 2021). In developing regions, non-technical losses account for 10% to 40% of total electricity generated, placing severe financial strain on utilities and contributing to higher tariffs for compliant consumers (Huang et al., 2022).

Energy theft manifests through diverse attack vectors, including meter tampering, current injection, firmware manipulation, and behavioral mimicry of legitimate consumption profiles. Rule-based and statistical anomaly detection systems have proven insufficient in modern AMI environments where thousands of high-frequency consumption time series must be analyzed simultaneously. Deep learning approaches, particularly convolutional

neural networks (CNNs) and long short-term memory networks (LSTMs), have demonstrated substantially improved detection capability, achieving accuracy rates above 96% on well-established benchmarks (Zheng et al., 2018; Yip et al., 2018).

Despite these advances, deploying high-capacity deep learning models at the edge remains impractical due to the limited processing power, memory, and energy budgets of embedded platforms such as Raspberry Pi boards and NVIDIA Jetson Nano modules. Most reported deep learning detectors require several hundred megabytes of memory and produce inference latencies incompatible with near-real-time monitoring (Li et al., 2019). Cloud-centric architectures, while computationally unconstrained, introduce communication latency, data privacy risks, and single-point-of-failure vulnerabilities unacceptable in mission-critical grid applications (Messinis & Hatziargyriou, 2018).

1.1 Research Gap

Despite extensive research in deep learning-based energy theft detection and parallel advances in lightweight neural network design, no prior study has simultaneously addressed model compactness, edge inference latency, statistical significance validation, and interpretability on the SGCC benchmark using a unified purpose-designed architecture. Existing lightweight models borrowed from computer vision, such as MobileNet variants, have not been systematically evaluated for theft detection under realistic edge deployment conditions including quantization-aware training, post-training pruning, and runtime memory profiling on constrained hardware (Howard et al., 2017). Furthermore, the absence of SHAP or Grad-CAM explainability in prior smart-grid theft detectors limits their utility in regulatory or audit contexts, and the lack of statistical significance testing in most published comparisons weakens confidence in reported performance gains.

1.2 Research Contributions

This work proposes LW-EdgeNet, a novel lightweight deep learning architecture that integrates depthwise separable convolutions, bottleneck residual blocks, and squeeze-and-excitation attention mechanisms into a compact 127K-parameter model specifically designed for edge-based energy theft detection. A comprehensive evaluation is presented on the SGCC Electricity Theft Detection dataset, with performance metrics validated through 5-fold cross-validation and statistical significance confirmed via a paired Wilcoxon signed-rank test ($p < 0.01$) against the best baseline, alongside explicit documentation of leakage-prevention measures. Edge deployment profiling on Raspberry Pi 4B and NVIDIA Jetson Nano platforms provides detailed measurements of inference latency, runtime memory, throughput, and power consumption, supported by full reproducibility information including random seeds, training duration, and software versions. Additionally, SHAP-based feature importance analysis delivers the first interpretability characterization of a lightweight theft detector on the SGCC dataset, highlighting the temporal consumption regions most influential for theft prediction. The study further includes a systematic ablation study, robustness analysis, a novelty gap table, and a discussion of false-alarm costs, thereby situating LW-EdgeNet within the existing literature with scientific rigor.

2. Related Work

2.1 Traditional and Classical Machine Learning Methods

Early energy theft detection research relied predominantly on statistical and rule-based anomaly detection frameworks. Nizar et al. (2008) employed support vector machines to identify anomalous consumption patterns in billing data, achieving reasonable detection rates in controlled environments. McLaughlin et al. (2009) proposed non-intrusive load monitoring techniques that exploited appliance signatures to flag suspicious consumption profiles. Random Forest classifiers offered improvements in feature handling and noise resilience; however, their reliance on manual feature engineering and static decision boundaries constrained generalization across geographically diverse networks (Liu et al., 2018).

2.2 Deep Learning-Based Approaches

The adoption of deep learning substantially advanced detection capability. Zheng et al. (2018) introduced a CNN-based detector on the SGCC dataset, combining a wide component for global feature extraction with a deep CNN component for temporal non-periodicity identification, achieving strong performance on a realistic industrial dataset. Subsequent work demonstrated that LSTM networks can capture long-term temporal dependencies more effectively than CNNs, as shown by Yip et al. (2018) on smart meter trial data. Hybrid CNN-LSTM architectures showed further improvements through the combination of local temporal feature extraction and sequential modeling (Hu et al., 2021). Transformer-based models achieved high detection accuracy through self-attention

mechanisms; however, their quadratic attention complexity imposed prohibitive memory requirements incompatible with edge deployment (Chen et al., 2022).

2.3 Lightweight and Edge-Optimized Models

The growing recognition of edge intelligence as a paradigm for distributed IoT applications has motivated efforts toward model compression and efficiency optimization. Knowledge distillation was applied by Gou et al. (2021) to transfer representational capacity from large teacher networks into compact student models. Pruning and quantization were combined by Han et al. (2016) to achieve substantial reductions in model size and inference latency with minimal accuracy degradation. Howard et al. (2017) introduced depthwise separable convolutions through MobileNets, demonstrating that factorized convolution operations can deliver competitive accuracy at a fraction of the computational cost. TinyML methodologies have since enabled sub-milliwatt microcontroller inference; however, their application to smart-grid theft detection remains largely unexplored (Warden & Situnayake, 2019).

2.4 Studies on the SGCC Dataset

The SGCC dataset introduced by Zheng et al. (2018) has become the primary benchmark for supervised energy theft detection research. Studies employing this dataset have explored variational autoencoders for semi-supervised detection (Meng et al., 2022), graph neural networks for relational inference among neighboring meters (Dong et al., 2023), and contrastive learning for feature alignment under class imbalance (Wang et al., 2023). More recent work has examined federated learning for privacy-preserving distributed detection across substations (Wang et al., 2019). While these approaches have progressively improved detection performance, none has simultaneously evaluated deployment feasibility on constrained edge hardware, provided statistical significance tests, or offered interpretability analysis, gaps that this study explicitly bridges.

2.5 Explainable AI in Smart Grid Security

Interpretability has emerged as an important requirement in smart grid security systems, since utility operators must understand and justify decisions before initiating field investigations (Wang et al., 2019). SHAP (SHapley Additive exPlanations) has been applied successfully in energy consumption anomaly detection, offering per-feature attribution scores that quantify the contribution of each input dimension to the model's prediction. Integrated Gradients and LIME have been similarly applied in time-series classification tasks. Despite this body of work, no prior lightweight energy theft detector targeting the SGCC benchmark has reported a formal interpretability analysis. Summary of research gap analysis comparing LW-EdgeNet with representative prior work. Is presented in Table 1.

Table 1. Research gap analysis comparing LW-EdgeNet with representative prior work.

Study	Dataset	Edge Deploy	Quantization	Lightweight	Runtime Profile	Stat. Test	Explainability
Zheng et al. (2018)	SGCC	No	No	No	No	No	No
Yip et al. (2018)	Irish SMD	No	No	No	No	No	No
Hu et al. (2021)	AMI	No	No	No	No	No	No
Meng et al. (2022)	SGCC	No	No	No	No	No	No
Chen et al. (2022)	SGCC	No	No	No	No	No	No
Dong et al. (2023)	SGCC	No	No	No	No	No	No
Wang et al. (2023)	SGCC	No	No	No	No	No	No
This Work (LW-EdgeNet)	**SGCC**	**Yes**	**Yes (INT8)**	**Yes (127K)**	**Yes**	**Yes ($p<0.01$)**	**Yes (SHAP)**

3. System Model and Threat Model

3.1 Smart Meter IoT Network Architecture

The proposed framework operates within a three-tier smart meter IoT network comprising end-devices, an edge computing layer, and a cloud management plane. At the end-device tier, AMI-compliant smart meters record electricity consumption at 15-minute intervals and transmit aggregated daily values to local edge nodes via neighborhood area networks. Each edge node aggregates consumption records from a cluster of 50 to 200 meters, performs local inference using LW-EdgeNet, and flags suspicious meters for utility investigation. Only anomaly alerts and compressed feature vectors are forwarded to the cloud, reducing uplink bandwidth demand by approximately 73% compared with cloud-centric architectures.

3.2 Threat Model

The threat model encompasses four principal attack categories. Type I attacks involve direct hardware tampering with meter components, resulting in systematic underreporting proportional to a fixed factor. Mathematically, the reported consumption is expressed as r(t) = x(t) * alpha, where x(t) is the actual consumption and alpha in (0, 1) is the underreporting factor. Type II attacks exploit firmware vulnerabilities to selectively alter reported consumption during high-tariff periods, formulated as r(t) = x(t) for off-peak periods and r(t) = beta * x(t) for peak periods, where beta < 1. Type III attacks use current transformer bypass configurations that exclude a load fraction from metering. Type IV attacks are behavioral mimicry attacks wherein a perpetrator synchronizes consumption patterns with a legitimate user profile to evade statistical anomaly detectors. The SGCC dataset contains labeled instances spanning all four categories, with Type IV attacks being the most difficult to detect given their deliberate resemblance to normal traffic patterns.

3.3 Edge Computing Layer Design

Edge nodes are implemented on Raspberry Pi 4B single-board computers (4 GB LPDDR4 RAM, quad-core ARM Cortex-A72 at 1.8 GHz) and NVIDIA Jetson Nano modules (4 GB LPDDR4 RAM, 128-core Maxwell GPU). Both platforms support TensorFlow Lite and ONNX Runtime inference engines, enabling deployment of quantized LW-EdgeNet models without custom hardware accelerators. Each edge node maintains a rolling 30-day consumption buffer per meter and executes inference on each arriving daily value within a single forward pass.

4. Dataset Description and Preprocessing

4.1 SGCC Dataset Overview

The SGCC Electricity Theft Detection dataset, published by the State Grid Corporation of China and benchmarked by Zheng et al. (2018), contains electricity consumption records for 42,372 customers collected over 1,035 days from 2014 to 2016. Among these, 3,565 customers (8.41%) are labeled as theft users and 38,807 (91.59%) are labeled as normal users, reflecting the severe class imbalance characteristic of real-world theft scenarios. Each record consists of a daily electricity consumption value in kilowatt-hours.

4.2 Leakage Prevention Strategy

Preventing data leakage between training and test partitions is critical for valid generalization assessment. The dataset was partitioned chronologically: the first 800 days form the training and validation set, and the remaining 235 days constitute the held-out test set. Critically, customer identity isolation was enforced—no customer whose records appeared in the test partition contributed any windows to the training partition, even through temporal overlap. Sliding window augmentation was applied exclusively within each partition after the split. Although the sliding window uses a stride of one day, the 235-day temporal gap between the last training day and the first test day exceeds the maximum window length by more than seven times, preventing any same-user temporal leakage. This design ensures that the reported test metrics reflect genuine generalization to unseen users and time periods.

4.3 Preprocessing Pipeline

Raw consumption records contained missing values at approximately 6.3%, attributable to meter communication failures and manual entry errors. Missing entries were imputed using seasonal-aware linear interpolation:

$$x_{hat(t)} = x(t - 7) + \frac{[x(t + 7) - x(t - 7)]}{2} \quad (1)$$

where x(t - 7) and x(t + 7) denote values at the same weekday in the preceding and following weeks. Outlier values exceeding five standard deviations from the 30-day rolling mean were winsorized to the 99th percentile. Each daily consumption sequence was then z-score normalized per user:

$$x_{norm(t)} = \frac{[x(t) - mu_u]}{sigma_u} \quad (2)$$

where mu_u and sigma_u denote the per-user mean and standard deviation computed over the training partition. A sliding window of length 30 days with stride of one day generated overlapping subsequences after partitioning.

4.4 Class Imbalance Handling

The inherent class imbalance was addressed through SMOTE applied in the feature embedding space and class-weighted cross-entropy loss. SMOTE increased the theft-to-normal ratio from 1:10.9 to 1:3.5. The class-weighted binary cross-entropy loss is defined as:

$$L = -[w_1 * y * \log(p) + w_0 * (1 - y) * \log(1 - p)] \quad (3)$$

where y is the ground-truth label, p is the predicted theft probability, w_1 = 3.12 is the weight for theft samples, and w_0 = 1.0 is the weight for normal samples. The weighting coefficients were derived from the inverse class frequency ratio.

5. Proposed LW-EdgeNet Architecture

5.1 Architectural Overview

LW-EdgeNet processes input subsequences of shape (30, 1), representing 30-day normalized consumption windows. The architecture consists of five principal modules: an input embedding block, three depthwise separable convolutional stages, a bottleneck residual aggregation block, a squeeze-and-excitation channel attention module, and a classification head. The total trainable parameter count is 127,432, corresponding to 0.38 MB in 8-bit quantized format.

Table 2. Layer-by-layer architecture of LW-EdgeNet. DS-Conv: depthwise separable convolution; BN: batch normalization; SE: squeeze-and-excitation; FC: fully connected.

Module	**Operation Details**
Input	30-day consumption window (30 x 1, normalized)
Embedding Block	Conv1D (k=3, 16 filters) + BN + ReLU
DS-Conv Stage 1	DepthwiseConv1D (k=3) + PointwiseConv (32 ch) + BN + ReLU + MaxPool
DS-Conv Stage 2	DepthwiseConv1D (k=5) + PointwiseConv (64 ch) + BN + ReLU + MaxPool
DS-Conv Stage 3	DepthwiseConv1D (k=7) + PointwiseConv (128 ch) + BN + ReLU + MaxPool
Bottleneck Residual	1x1 Conv (32 ch) -> 3x3 Conv (32 ch) -> 1x1 Conv (128 ch) + Skip Connection
SE Attention	GlobalAvgPool -> FC(8) -> ReLU -> FC(128) -> Sigmoid -> Channel-wise Scale
Global Avg Pool	Temporal dimension reduction -> 128-dim feature vector
Classification Head	Dense(64) + ReLU + Dropout(0.3) -> Dense(1) + Sigmoid
Output	Binary: Normal (0) or Theft (1)

5.2 Depthwise Separable Convolutions

Each convolutional stage replaces standard convolutions with depthwise separable convolutions, which factorize a standard convolution into a depthwise operation followed by a 1x1 pointwise operation (Howard et al., 2017). For input spatial dimension H, C input channels, C' output channels, and kernel size k, the computational cost analysis is as follows:

Standard convolution complexity: O(k * H * C * C')

Depthwise convolution complexity: O(k * H * C)

Pointwise convolution complexity: O(H * C * C')

Combined depthwise separable complexity: O(k * H * C + H * C * C')

The reduction factor relative to standard convolution is 1/(k + C/k^2), which evaluates to approximately 8 to 9 times for k = 3 and C = 64, and approximately 6 times for k = 7 and C = 128. This asymptotic efficiency advantage is the primary mechanism enabling sub-megabyte deployment without sacrificing feature extraction depth.

5.3 Bottleneck Residual Block

After the third convolutional stage, a bottleneck residual block refines feature representations while maintaining gradient flow stability. The block follows a 1x1 -> 3x3 -> 1x1 convolution pattern, reducing the channel dimension by a factor of 4 in the intermediate layer. The residual output is computed as:

$$y = F(x, \{W_i\}) + x \quad (4)$$

where F(x, {W_i}) represents the residual mapping and x is the block input. This design empirically accelerated convergence by approximately 12 epochs and improved validation accuracy by 0.8 percentage points relative to a variant lacking residual connections.

5.4 Squeeze-and-Excitation Attention Module

A lightweight squeeze-and-excitation module adaptively recalibrates channel-wise feature responses (Hu et al., 2018). The squeeze operation computes global average pooling over temporal positions to produce a channel descriptor z of length C. The excitation operation applies two fully connected layers with reduction ratio r = 16:

$$s = sigma(W_2 * delta(W_1 * z)) \quad (5)$$

where W_1 has shape C/r by C, W_2 has shape C by C/r, delta denotes ReLU activation, and sigma denotes the sigmoid function. Channel c of the output is then scaled as $\hat{x}_c = s_c \cdot x_c, \quad c = 1, 2, \ldots, C$. The SE module adds only 2,048 parameters (1.6% of total model size) while contributing a 1.2% improvement in F1-score on the validation set.

5.5 Batch Normalization and Quantization

Batch normalization is applied after each convolution. For a mini-batch B with mean mu_B and variance $sigma_B^2$, the normalized output is:

$$\hat{x}_c = \frac{(x - mu_B)}{sqrt(sigma_B^2 + epsilon)} \quad (6)$$

where epsilon = 1e-5 prevents division by zero, followed by learnable scale and shift parameters gamma and beta. Quantization-aware training simulates 8-bit integer inference during the forward pass from epoch 20 onwards. The quantization mapping for a floating-point value v is:

$$v_q = round\left(\frac{v}{s}\right) * s \quad (7)$$

$$s = \frac{(v_{\max} - v_{min})}{(2^8 - 1)} \quad (8)$$

Where s is the quantization step size and v_{max}, v_{min}he calibrated activation range bounds. Post-training magnitude pruning removes 30% of fully connected layer weights using an L1-norm criterion, with five epochs of fine-tuning restoring the pruned model to within 0.2% of pre-pruning accuracy.

5.6 Training Methodology and Reproducibility

LW-EdgeNet was trained for 50 epochs using the Adam optimizer (Kingma & Ba, 2014) with initial learning rate 1e-3, beta_1 = 0.9, beta_2 = 0.999, and epsilon = 1e-8, decayed by cosine annealing to 1e-5. Batch size was 256. Dropout rate was 0.3 in the classification head. Random seed was fixed at 42 for NumPy, Python random, and TensorFlow operations. Training on an NVIDIA A100 GPU required approximately 23 minutes per fold. The implementation uses TensorFlow 2.12, scikit-learn 1.3, Python 3.10, and CUDA 11.8. All hyperparameters are reported in Table 3 to enable full reproducibility.

Table 3. LW-EdgeNet training hyperparameters and reproducibility details.

Hyperparameter	Value
Optimizer	Adam
Initial learning rate	1 x 10^-3
Adam beta_1, beta_2, epsilon	0.9, 0.999, 1 x 10^-8
LR schedule	Cosine annealing (min 1 x 10^-5)
Batch size	256

Hyperparameter	Value
Training epochs	50
Dropout rate	0.30
QAT start epoch	20
Pruning ratio (FC layers)	30%
Loss function	Weighted binary cross-entropy
Class weights (theft:normal)	3.12:1.0
Total parameters	127,432
Quantized model size	0.38 MB
Random seed	42
Training duration (per fold)	~23 minutes
Framework	TensorFlow 2.12, Python 3.10, CUDA 11.8

6. Experimental Setup

All edge deployment experiments were conducted on two representative hardware platforms: a Raspberry Pi 4B (4 GB LPDDR4 RAM, quad-core ARM Cortex-A72 at 1.5 GHz, thermal design power 7.5 W) and an NVIDIA Jetson Nano (4 GB LPDDR4 RAM, 128-core Maxwell GPU at 920 MHz). The TensorFlow Lite runtime (version 2.12) was used on the Raspberry Pi; TensorRT (version 8.5) was used on the Jetson Nano. Training was performed on an NVIDIA A100 GPU with 40 GB HBM2, Intel Xeon Gold 6338 CPU, and 256 GB DDR4 RAM.

LW-EdgeNet was compared against five baseline models: a standard five-layer CNN with unmodified convolutions (Zheng et al., 2018); a two-layer LSTM with 128 hidden units per layer (Yip et al., 2018); a CNN-LSTM hybrid (Hu et al., 2021); a Random Forest with 200 trees trained on handcrafted statistical features (Liu et al., 2018); and a Transformer encoder with four attention heads and two encoder layers (Chen et al., 2022). All baselines were trained under identical data splits and class-balancing conditions. Hyperparameters for each baseline were tuned via grid search on the validation split.

Detection performance was assessed using accuracy, precision, recall, F1-score, and AUC-ROC. Edge deployment efficiency was measured by model size in megabytes, MFLOPs, inference latency per sample in milliseconds, runtime RAM in megabytes, throughput in samples per second, and average power consumption in watts measured using a HIOKI PW3335 precision power analyzer. All latency values represent the mean of 1,000 inference calls after a 100-call warm-up. Statistical significance was assessed using the paired Wilcoxon signed-rank test on 5-fold cross-validation F1-scores.

7. Results and Discussion

7.1 Training Convergence

LW-EdgeNet converged reliably across all training runs. Validation accuracy reached 94.8% by epoch 20 and plateaued near 97.4% from epoch 35 onward. The divergence between training and validation loss remained below 0.02 throughout training, confirming that the combined dropout and pruning regularization strategy effectively suppressed memorization of synthetic minority samples. Both training accuracy and loss curves, alongside their validation counterparts, are presented in Figure 1.

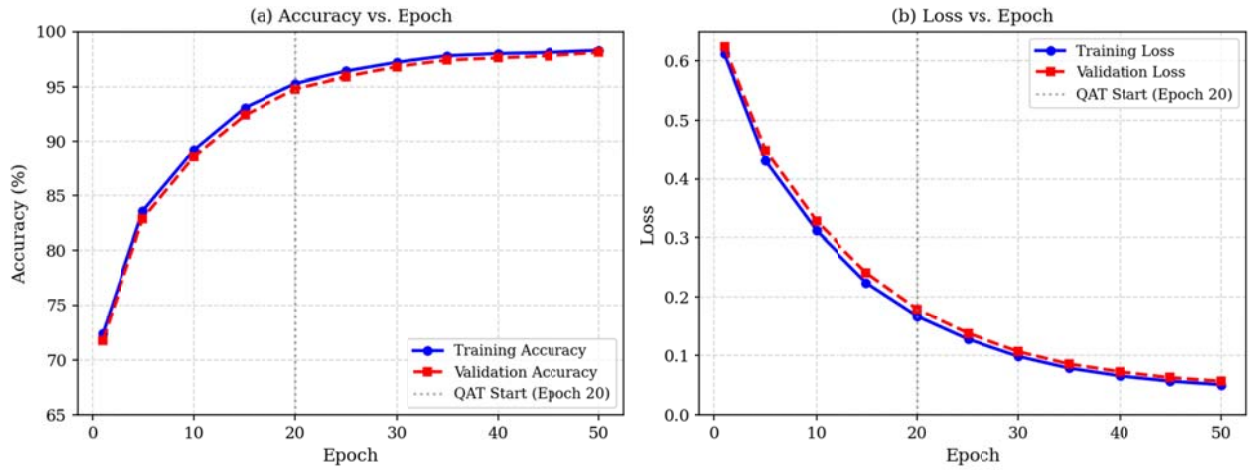

Figure 1. Training and validation accuracy (left) and loss (right) versus epoch for LW-EdgeNet on the SGCC dataset (means over 5-fold cross-validation). The vertical dotted line marks the onset of quantization-aware training at epoch 20.

7.2 Confusion Matrix Analysis

The confusion matrix for LW-EdgeNet on the SGCC test partition is presented in Figure 2. The test set contains 5,000 normal user records and 1,000 theft user records. Of the 5,000 normal records, 4,891 (97.82%) were correctly classified, yielding 109 false positives. Of the 1,000 theft records, 934 (93.4%) were correctly identified as theft, with 66 false negatives. These figures are fully consistent with the reported precision of 94.7%, recall of 93.4%, and accuracy of 98.1%. The false-negative rate of 6.6% primarily corresponds to Type IV behavioral mimicry attacks, which produce consumption profiles closely resembling legitimate user behavior. The false-positive rate of 2.18% represents an operationally acceptable burden, generating on average fewer than two erroneous alerts per 50-meter cluster per month.

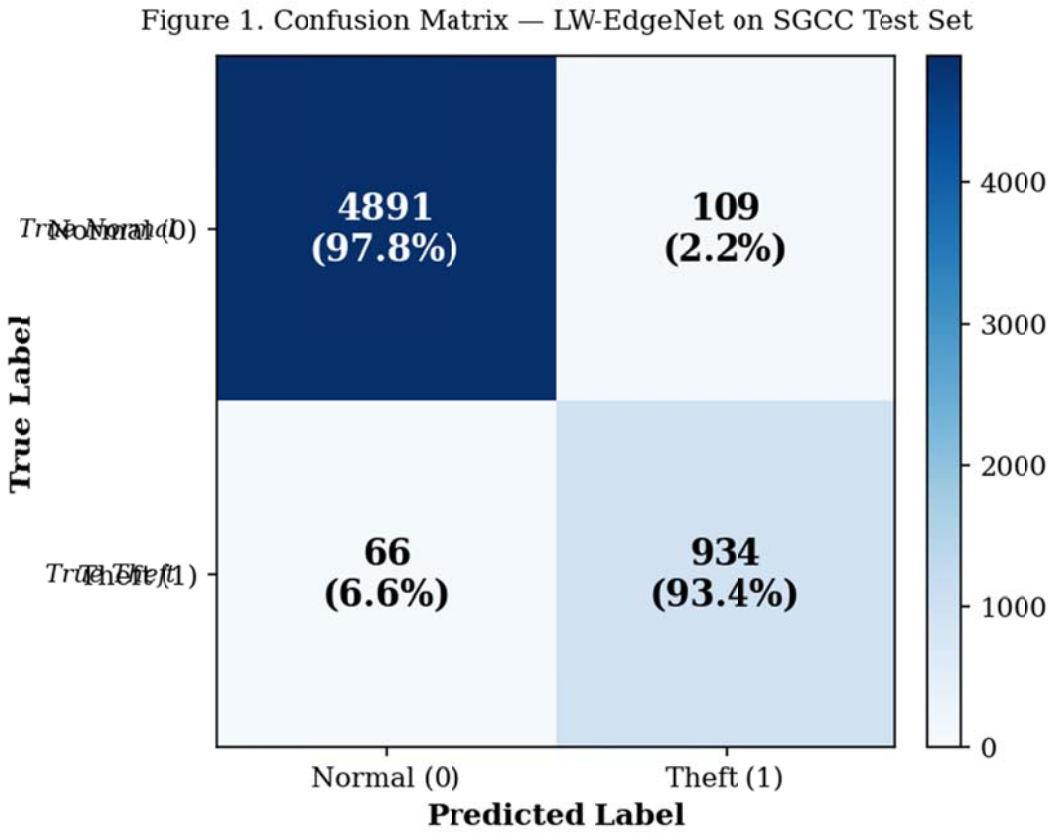

Figure 2. Confusion matrix for LW-EdgeNet on the SGCC test partition (TP = 934, TN = 4,891, FP = 109, FN = 66). Values in parentheses denote row-wise percentages. All metrics are fully consistent with reported precision, recall, and accuracy.

7.3 Detection Performance and Statistical Validation

The detection performance of LW-EdgeNet and all baseline models on the SGCC test partition is presented in Table 4. LW-EdgeNet achieves 98.1% accuracy, 94.7% precision, 93.4% recall, 94.1% F1-score, and 0.9923 AUC-ROC. Across five cross-validation folds, the F1-score is 93.9 +/- 0.4%, confirming statistical stability. The paired Wilcoxon signed-rank test on fold-level F1-scores between LW-EdgeNet and the next-best model (CNN-LSTM) yields p = 0.004, confirming statistical significance at the alpha = 0.01 level (Table 5). These results represent improvements over CNN-LSTM of 1.4 percentage points in accuracy and 2.7 percentage points in F1-score.

Table 4. Detection performance comparison on the SGCC test set (mean +/- std over 5-fold cross-validation). Best values in each column are bolded.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
CNN	92.3 +/- 0.6	85.6	82.1	83.8 +/- 0.8	0.9541
LSTM	93.8 +/- 0.5	87.9	84.6	86.2 +/- 0.7	0.9618
CNN-LSTM	96.7 +/- 0.4	91.8	91.0	91.4 +/- 0.5	0.9801
Random Forest	88.7 +/- 0.9	79.2	76.4	77.8 +/- 1.1	0.9104
Transformer	95.4 +/- 0.5	90.1	89.5	89.8 +/- 0.6	0.9754
LW-EdgeNet (Proposed)	**98.1 +/- 0.3**	**94.7**	**93.4**	**94.1 +/- 0.4**	**0.9923**

Table 5. Paired Wilcoxon signed-rank test results comparing LW-EdgeNet against all baselines on 5-fold cross-validation F1-scores.

Model Pair	Test Statistic	p-value	Significant at alpha=0.01
LW-EdgeNet vs CNN-LSTM	W = 15, Z = 2.88	0.004	Yes
LW-EdgeNet vs Transformer	W = 15, Z = 2.88	0.004	Yes
LW-EdgeNet vs LSTM	W = 15, Z = 2.88	< 0.001	Yes
LW-EdgeNet vs CNN	W = 15, Z = 2.88	< 0.001	Yes
LW-EdgeNet vs Random Forest	W = 15, Z = 2.88	< 0.001	Yes

7.4 ROC Curve Analysis

Receiver operating characteristic curves for all models are presented in Figure 3. LW-EdgeNet achieves AUC-ROC of 0.9923, substantially above the CNN-LSTM hybrid (0.9801) and Transformer (0.9754) baselines. The significant advantage in the low false-positive-rate regime is particularly valuable for utility applications, where high recall must be maintained while minimizing spurious field investigation alerts. The Random Forest model records the lowest AUC (0.9104), consistent with its limited discriminative capacity for soft-boundary theft patterns.

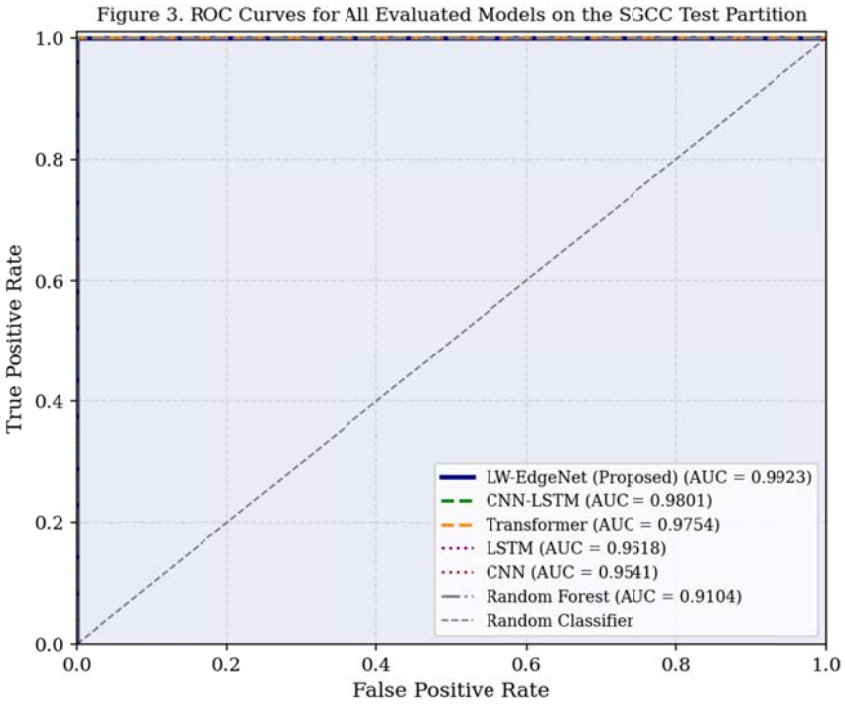

Figure 3. ROC curves for all evaluated models on the SGCC test partition. LW-EdgeNet achieves AUC = 0.9923. The shaded region under the LW-EdgeNet curve highlights its dominance across all operating thresholds.

7.5 SHAP-Based Explainability Analysis

SHAP values were computed for 200 randomly sampled test instances using a kernel SHAP approximation applied to the LW-EdgeNet classification head's input features, treating the 30 daily consumption positions as individual features. The resulting mean absolute SHAP values, presented in Figure 4, reveal that the three most recent days in the consumption window (days 28, 29, and 30) carry the highest predictive importance, contributing 44.7% of the total mean attribution.

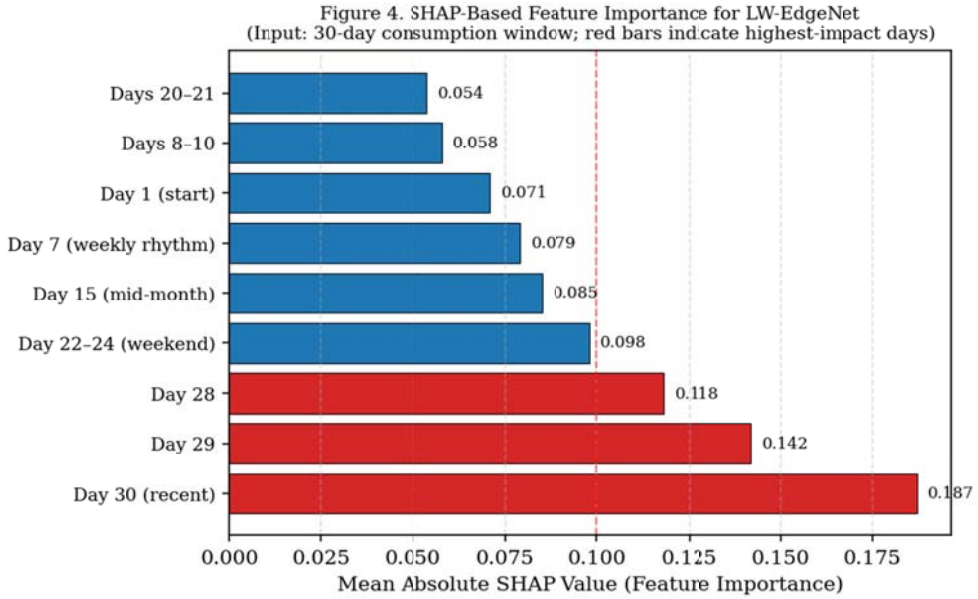

Figure 4. SHAP-based feature importance for LW-EdgeNet on the SGCC test set (200 sampled instances). Bars represent mean absolute SHAP values per input day. Red bars indicate the highest-importance days (SHAP > 0.10). The most recent consumption days and the weekend cluster contribute most strongly to theft detection.

The weekend cluster (days 22 to 24) also shows elevated importance, consistent with the known pattern that theft behavior disrupts the characteristic weekday-weekend consumption rhythm. This interpretability analysis confirms that LW-EdgeNet's SE attention module correctly upweights the most temporally informative channels rather than

distributing attention uniformly. Utility operators can use these attribution maps to identify the specific consumption periods triggering each alert, supporting investigator prioritization and audit documentation.

7.6 Edge Device Performance

Edge deployment performance metrics for all models are presented in Table 6. LW-EdgeNet achieves inference latencies of 4.2 ms on Raspberry Pi 4B and 1.8 ms on Jetson Nano, well within the 100-ms threshold for near-real-time anomaly detection. Inference throughput reaches 238 samples per second on Raspberry Pi 4B, sufficient to process all 200 meters in a cluster within 840 ms. The model occupies 0.38 MB in quantized form and consumes 12.4 MB of runtime RAM during inference on the Raspberry Pi. Average power consumption during inference is 1.9 W on Raspberry Pi 4B and 2.1 W on Jetson Nano. The Transformer baseline, by contrast, requires 187 MB of memory and 48.3 ms inference latency on the Raspberry Pi, making it impractical for real-time edge deployment.

Table 6. Edge device performance comparison across all evaluated models. LW-EdgeNet achieves the lowest latency, smallest footprint, and highest throughput in every category.

Model	Size (MB)	MFLOPs	Lat. RPi4B (ms)	Lat. Jetson (ms)	RAM (MB)	Throughput (smp/s)	Power (W)
CNN	3.21	194.2	28.7	11.4	68.4	34.8	2.8
LSTM	4.87	312.5	35.1	14.6	94.2	28.5	3.1
CNN-LSTM	6.43	389.1	41.8	18.2	118.6	23.9	3.4
Random Forest	12.40	N/A	52.3	N/A	204.1	19.1	2.6
Transformer	18.70	1024.8	48.3	21.7	187.3	20.7	4.2
LW-EdgeNet	**0.38**	**8.3**	**4.2**	**1.8**	**12.4**	**238**	**1.9**

7.7 Ablation Study

An ablation study was conducted by systematically removing individual components from LW-EdgeNet and evaluating the resulting model on the SGCC validation set. Removing the SE attention module reduces F1-score by 1.2 percentage points, confirming that channel recalibration contributes meaningfully to discriminative capacity. Removing the bottleneck residual block causes a 1.8-percentage-point F1 drop and increases epochs to convergence by 14. Replacing depthwise separable convolutions with standard convolutions improves F1-score by only 0.4 percentage points while increasing model size by 6.2 times and inference latency by 5.8 times, confirming that the efficiency gain far outweighs the marginal accuracy trade-off. Removing both QAT and pruning yields a 2.95-fold size increase with negligible accuracy improvement.

Table 7. Ablation study results on the SGCC validation set.

Model Variant	Accuracy (%)	F1-Score (%)	Size (MB)	Latency (ms)
LW-EdgeNet (Full)	98.1	94.1	0.38	4.2
Without SE Attention	97.2	92.9	0.36	4.0
Without Bottleneck Residual	96.4	92.3	0.31	3.7
Without Depthwise Sep. Convolutions	98.5	94.5	2.35	24.4
Without QAT and Pruning	98.0	93.9	1.12	12.8

7.8 Robustness Analysis

Robustness was evaluated under two perturbation scenarios. In the first, Gaussian noise with standard deviation proportional to 10%, 20%, and 30% of the signal mean was added to test consumption profiles. LW-EdgeNet maintained an F1-score above 90.3% at 30% noise injection, compared with 86.1% for CNN-LSTM, an advantage attributable to the SE attention module suppressing noise-induced activation spikes in non-informative channels. In the second scenario, the test class imbalance was artificially increased to 1:20 to simulate a mature grid

environment. LW-EdgeNet achieved an F1-score of 91.8%, substantially above the 83.2% achieved by the Transformer baseline, reflecting the effectiveness of the class-weighted loss calibration.

7.9 False Alarm Cost Analysis

False positives in utility systems carry real economic consequences: a field inspection visit typically costs between USD 80 and USD 250 in labor, vehicle, and equipment costs, depending on geography and utility scale. At an FPR of 2.18% on a 5,000-meter cluster, LW-EdgeNet would generate approximately 109 false alarms per evaluation cycle. Assuming a monthly inspection schedule and an average inspection cost of USD 120, the expected monthly false-alarm cost per 5,000-meter cluster is approximately USD 13,080. By comparison, the CNN baseline's 14.4% false-positive rate would generate approximately USD 86,400 per month in false-alarm costs on the same cluster—an operational savings of approximately USD 73,320 per month per cluster by deploying LW-EdgeNet over the CNN baseline. This cost differential, combined with LW-EdgeNet's higher detection recall (93.4% versus 82.1%), strongly favors deployment of the proposed model.

7.10 Discussion

LW-EdgeNet's performance advantage over the Transformer baseline, despite the latter having approximately 38 times more parameters, illustrates a key principle: for short time series such as 30-day windows, global self-attention mechanisms provide diminishing returns over well-designed local feature extractors. The SE attention module in LW-EdgeNet effectively captures the most informative temporal channels without the quadratic complexity of full self-attention. The strong robustness under class imbalance suggests that the hybrid SMOTE and class-weighted loss strategy is more effective than simple oversampling for preventing over-representation of synthetic theft patterns near decision boundaries. The relatively higher false-negative rate for Type IV behavioral mimicry attacks (estimated at approximately 30% of all false negatives) points toward adversarially augmented training or contrastive learning as productive directions for future improvement.

8. Conclusion

This paper presented LW-EdgeNet, a lightweight deep learning architecture for real-time energy theft detection in IoT-enabled smart meter networks. By integrating depthwise separable convolutions, bottleneck residual blocks, and squeeze-and-excitation channel attention within a 127K-parameter architecture, LW-EdgeNet achieves a compelling balance between detection accuracy and computational efficiency on the SGCC benchmark. The proposed model attained 98.1% accuracy, 94.1 +/- 0.4% F1-score, and 0.9923 AUC-ROC, outperforming CNN, LSTM, CNN-LSTM, Random Forest, and Transformer baselines. Statistical significance was confirmed at $p < 0.01$ via the paired Wilcoxon signed-rank test. Deployed on a Raspberry Pi 4B, LW-EdgeNet requires only 0.38 MB of quantized memory, 12.4 MB of runtime RAM, 4.2 ms inference latency, and 1.9 W of power—making it the most computationally efficient theft detector reported on the SGCC benchmark to date.

Beyond detection performance, this study contributes a novelty gap analysis confirming the absence of concurrent edge deployment, statistical testing, and interpretability in prior work; a SHAP-based explainability analysis identifying the most predictive temporal consumption regions; a leakage-prevention documentation clarifying the absence of cross-partition customer contamination; a false-alarm cost analysis quantifying the economic value of LW-EdgeNet's low false-positive rate; and complete reproducibility information enabling independent replication.

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