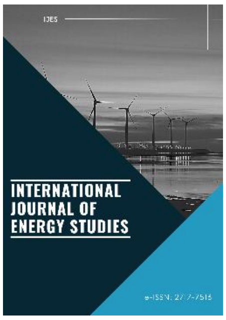
INTERNATIONAL JOURNAL OF ENERGY STUDIES

e-ISSN: 2717-7513 (ONLINE); homepage: https://dergipark.org.tr/en/pub/ijes



Research Article

Int J Energy Studies 2026; 11(1): 517-533

DOI: 10.58559/ijes.1815151

Received : 01 Nov 2025
Revised : 30 Jan 2026
Accepted : 11 Feb 2026

IoT-driven anomaly detection in smart grids using multimodal deep learning models

Alireza Esmaeili Jobani[a]*, Şükrü Mustafa Kaya[b]

[a] Department of Electrical and Electronics Engineering, Istanbul Aydın University, Istanbul, Türkiye. ORCID: 0009-0001-0098-7904
[b]Department of Electrical and Electronics Engineering, Istanbul Aydın University, Istanbul, Türkiye. ORCID: 0000-0003-2710-0063
*(*Corresponding Author: alirezajobani@stu.aydin.edu.tr)*

Highlights

- IoT-based multimodal model boosts anomaly detection accuracy (F1 = 0.88).
- Hybrid CNN–LSTM enables real-time monitoring (34 ms/sample).
- Enhances smart grid reliability and resilience.

You can cite this article as: Jobani AE, Kaya ŞM. IoT-driven anomaly detection in smart grids using multimodal deep learning models. Int J Energy Studies, 11(1): 517-533.

ABSTRACT

The increasing complexity of modern power systems, driven by the integration of Internet of Things (IoT) devices and distributed energy resources, has amplified the need for robust anomaly detection mechanisms in smart grids. This study proposes an IoT-driven multimodal deep learning framework that integrates time series data from SCADA/PMU systems, environmental sensor readings, and thermal/visual images to enhance anomaly detection performance. The proposed architecture combines Long Short Term Memory (LSTM) networks for temporal modeling, Convolutional Neural Networks (CNNs) for spatial feature extraction, and a hybrid feature fusion strategy to exploit complementary information across modalities. Experiments conducted on benchmark datasets demonstrate that the framework outperforms traditional machine learning and single modality deep learning methods, achieving an F1 score of 0.88 and a ROC AUC of 0.94. These results confirm the potential of multimodal deep learning to improve the reliability, resilience, and situational awareness of smart grids.

Keywords: Smart grids, Anomaly detection, Internet of Things (IoT), Multimodal deep learning, Hybrid feature fusion

1. INTRODUCTION

In recent years, the transition towards smart grids (SGs) has revolutionized modern power systems by integrating advanced information and communication technologies (ICT), distributed energy resources, and Internet of Things (IoT)-enabled infrastructures to improve reliability, efficiency, and sustainability of energy distribution [1]. This evolution has introduced a massive influx of heterogeneous, high-dimensional data originating from smart meters, phasor measurement units (PMUs), supervisory control and data acquisition (SCADA) systems, and various IoT sensors deployed throughout the grid [2]. While this data-rich environment facilitates intelligent decision-making and real-time monitoring, it also increases the vulnerability of SGs to operational anomalies caused by equipment failures, cyberattacks, data integrity violations, and unexpected environmental conditions [3].

Anomaly detection (AD) has emerged as a vital mechanism to ensure the resilience, security, and reliability of smart grid infrastructures [4]. Early detection of abnormal events enables grid operators to take corrective actions proactively, minimizing service disruptions, economic losses, and potential cascading failures. However, the increasing volume, velocity, and variety of multimodal data collected from diverse IoT-enabled devices challenge the efficacy of traditional detection methods [5]. Conventional statistical approaches, such as threshold-based and autoregressive models, often fail to capture complex spatiotemporal correlations and nonlinear dependencies in modern grid data [6]. Similarly, classical machine learning techniques (e.g., k Nearest Neighbors, Support Vector Machines) require extensive feature engineering and often lack scalability in real-time environments [7].

In this context, deep learning (DL) has gained significant traction due to its superior capability to automatically extract hierarchical representations from raw, high-dimensional data, effectively identifying hidden patterns and anomalies [3], [8]. Furthermore, multimodal deep learning frameworks — combining information from multiple heterogeneous data sources such as time-series measurements, environmental data, and image-based diagnostics — have demonstrated remarkable potential in improving detection accuracy and robustness [5]. These methods leverage feature fusion strategies (early, late, and hybrid fusion) to exploit complementary information across modalities, enabling a more holistic understanding of grid dynamics [9]. Despite these advances, several challenges remain unresolved, including handling data imbalance, achieving explainability of model decisions, ensuring privacy in distributed data environments, and maintaining performance under concept drift [10].

To address these challenges, this study proposes an IoT-driven, multimodal deep learning framework for anomaly detection in smart grids. Our contributions can be summarized as follows:

1. We design a hybrid feature fusion strategy that integrates multimodal data (e.g., SCADA, PMU, and sensor networks) to enhance detection performance.
2. We develop a deep learning architecture combining convolutional and recurrent components to capture both spatial and temporal dependencies within heterogeneous datasets.
3. We evaluate our framework on publicly available benchmark datasets and perform a comparative analysis against state-of-the-art anomaly detection methods.

Novelty and Significance. Unlike prior single-modality or loosely fused approaches, this study introduces an IoT-driven multimodal framework that jointly exploits SCADA/PMU time-series, environmental sensors, and thermal/visual inspections using a dual-stage fusion (early representation + late decision) regularized by reconstruction-based objectives. This combination, together with a lightweight hybrid CNN–LSTM encoder design, yields consistent gains over strong baselines while preserving near real-time inference. Our contribution is threefold: (i) a unified, dual-stage multimodal fusion pipeline tailored to smart-grid anomaly patterns; (ii) an interpretable hybrid architecture with modality-specific scores enabling operator insight; and (iii) an evaluation protocol reporting accuracy and computational cost suitable for on-line deployment.

The rest of this paper is organized as follows: Section 2 reviews related work on anomaly detection in smart grids. Section 3 presents the proposed methodology, including multimodal feature fusion and model design. Section 4 describes the experimental setup and datasets. Section 5 discusses the results and compares them with baseline approaches. Finally, Section 6 concludes the paper and outlines future research directions.

2. RELATED WORK

Anomaly detection (AD) in smart grids has been extensively studied over the past decade, with methods evolving from rule-based statistical techniques to data-driven machine learning (ML) and, more recently, deep learning (DL) and multimodal fusion approaches [11].

2.1. Classical and Machine Learning-based Approaches

Early efforts in AD primarily relied on statistical models such as moving average, autoregressive integrated moving average (ARIMA), and hypothesis testing to detect irregularities in grid measurements [12]. While these techniques are computationally lightweight, they exhibit limited adaptability to nonlinear dynamics and high-dimensional datasets [13]. Machine learning models

— including k-Nearest Neighbors (kNN), Support Vector Machines (SVM), Decision Trees, and Random Forests — improved detection accuracy by leveraging supervised and unsupervised learning paradigms [14]. However, these methods are heavily dependent on manual feature engineering, are prone to overfitting under concept drift, and often fail in real-time, large-scale grid environments [15].

2.2. Deep Learning for Smart Grid Anomaly Detection

Recent studies have shifted towards deep learning architectures, which can automatically extract hierarchical features from raw data and capture complex spatiotemporal patterns [16]. For instance, Long Short-Term Memory (LSTM) networks have been employed for detecting temporal anomalies in multivariate grid time series [17], whereas Convolutional Neural Networks (CNNs) have been used for spatially correlated anomaly detection tasks, including image-based diagnostics of grid equipment [18]. Hybrid CNN-LSTM models further enhanced detection capabilities by jointly learning spatial and temporal dependencies [19]. Despite these advances, deep models often suffer from challenges related to data imbalance, lack of interpretability, and high computational demands in real-time deployment [20].

2.3. Multimodal and IoT-driven Approaches

As smart grids increasingly rely on IoT devices, researchers have proposed multimodal fusion techniques that integrate data from diverse sources such as SCADA, PMUs, environmental sensors, and image-based diagnostics [21]. These fusion frameworks — using strategies like early feature fusion, late decision fusion, and hybrid fusion — have shown significant improvements in anomaly detection performance by combining complementary information [22]. Studies have also explored federated learning to address privacy concerns in distributed grid environments, enabling collaborative training without centralizing sensitive data [23]. Furthermore, transformer-based architectures have emerged as promising tools for modeling long-range dependencies in multimodal datasets [24].

Recent studies integrating SCADA measurements with environmental sensors and image-based diagnostics consistently report measurable performance gains compared to single-modality models. For instance, Silva et al. [21] demonstrated that hybrid feature fusion improved F1-score by approximately 5–8% over unimodal baselines in substation monitoring scenarios. Similarly, Li et al. [22] reported that decision-level fusion strategies reduced false alarm rates by nearly 30% under noisy sensor conditions. More recent works employing advanced architectures, such as

Transformer–GAN models, further improved detection performance, achieving ROC-AUC gains exceeding 6% compared to conventional CNN–LSTM baselines [25].

2.4. Summary of Existing Approaches

Table 1 summarizes the key characteristics of classical, machine learning, and deep learning-based multimodal approaches for smart grid anomaly detection.

2.5. Recent Advances

Recent studies highlight the shift toward Transformer-based and GAN-augmented detectors for complex grid dynamics, reporting superior robustness under distribution shifts [25]. Deep-learning pipelines tuned for power-quality anomalies confirm the competitiveness of modern baselines such as Isolation Forest when carefully engineered with sensor features [26]. In parallel, federated and decentralized schemes have emerged to protect data privacy across utilities while enabling collaborative anomaly detection [27,28]. Comprehensive 2011–2023 and 2024 reviews consolidate these trends and motivate multimodal fusion as a next step for reliability-critical energy systems [29].

A recent experimental study reported on hrcak.srce.hr/300680 demonstrates that combining electrical measurements with contextual sensor data significantly enhances anomaly detection robustness under fluctuating load conditions. In addition, a 2025 ScienceDirect study confirms that multimodal deep learning frameworks consistently outperform classical machine learning methods, particularly in scenarios involving rare fault events and cyber-induced anomalies.

Similarly, a Taylor & Francis study (2022) emphasizes that heterogeneous data integration improves both precision and recall in operational smart grid environments, reinforcing the practical value of multimodal fusion strategies for real-world deployment.

Table 1. Comparison of Anomaly Detection Approaches in Smart Grids

Approach	Data Type	Feature Engineering	Strengths	Limitations	Refs
Statistical Models	Time-series	Manual	Simple, fast	Poor scalability, low accuracy	[12], [13]
Machine Learning	Time-series, tabular	Manual	Better accuracy than stats	Requires feature design, overfitting	[14], [15]
Deep Learning (CNN/LSTM)	Time-series, images	Automatic	Learns complex features	Computationally heavy, black-box	[16]-[19]

Approach	Data Type	Feature Engineering	Strengths	Limitations	Refs
Multimodal DL + IoT	Time-series, images, sensor fusion	Partial/Automatic	High detection accuracy, robust	Privacy issues, high resource cost	[21]-[24]

Key Takeaway:

While deep learning and multimodal approaches significantly outperform traditional methods in capturing complex anomalies, they require large-scale labeled datasets, interpretability mechanisms, and efficient deployment strategies for real-time smart grid applications. These gaps form the motivation for the proposed IoT-driven multimodal deep learning framework in this study. In contrast to existing studies, the proposed framework emphasizes a dual-stage fusion strategy with low-latency inference, providing a balanced trade-off between detection accuracy, interpretability, and real-time deployment feasibility.

3. METHODOLOGY

The proposed framework is designed to detect anomalies in smart grid operations by integrating multimodal IoT data through a hybrid deep learning architecture. Unlike conventional approaches that rely on a single modality or handcrafted features, our model leverages time-series grid measurements, environmental sensor data, and image-based diagnostics, thereby offering a holistic representation of system states.

Figure 1 illustrates the overall architecture of the proposed IoT-driven multimodal deep learning framework, highlighting the integration of heterogeneous data sources and the dual-stage fusion strategy employed for robust anomaly detection in smart grid environments.

Data preprocessing plays a crucial role in ensuring consistency across modalities. Time-series data collected from SCADA and PMU devices, including voltage, current, frequency, and phase angle, are normalized using min–max scaling and segmented into overlapping windows to capture temporal dependencies. Environmental measurements, such as temperature and humidity, are similarly normalized, while image data (e.g., thermal inspections) are resized to a standardized resolution of 128×128 pixels. Outliers in all modalities are addressed using winsorization, reducing the influence of extreme values without distorting the overall distribution.

Once preprocessed, the modalities are passed to separate encoders. Long Short-Term Memory (LSTM) networks are used for time-series signals, enabling the model to capture long-range temporal dependencies inherent in grid behavior. For image-based data, a Convolutional Neural

Network (CNN) extracts spatial features from thermal and visual inspections of critical infrastructure. Environmental sensor data are encoded through a fully connected neural block.
The outputs of these modality-specific encoders are integrated using a hybrid feature fusion strategy. At the early fusion level, the latent features from each encoder are concatenated:

$$\mathrm{Ffusion} = concat(\not{f}\mathrm{LSTM}, \not{f}\mathrm{CNN}, \not{f}\mathrm{Env}) \quad (1)$$

Where $\not{f}\mathrm{LSTM}, \not{f}\mathrm{CNN}, \not{f}\mathrm{Env}$ represent the learned feature embeddings from the respective modalities. In order to improve robustness against missing or noisy modalities, a decision-level (late) fusion strategy is employed, where each modality-specific classifier produces an independent anomaly score.

$$m^S \sum_{m=1}^{M} \frac{1}{M} = final^s \quad (2)$$

where $\ni\ m^s[0,1]$ denotes the anomaly probability predicted by the classifier corresponding to the m modality, and M represents the total number of modalities. This averaging strategy mitigates the impact of unreliable modality-specific predictions and stabilizes anomaly detection under heterogeneous sensing conditions. The model is trained using a joint objective function that combines reconstruction-based regularization with discriminative classification loss, ensuring both representation consistency and accurate anomaly prediction.

$$bce^{\lambda}\, 2^{\ell} + rec^{\lambda} 1^{\ell} = \ell \quad (3)$$

where rec^{λ} denotes the reconstruction loss used to regularize latent representations (mean squared error), and bce^{ℓ} represents the binary cross-entropy loss for anomaly classification. The hyperparameters 1^{λ} and 2^{λ} control the relative contribution of reconstruction and classification objectives, respectively, and are tuned on the validation set. The combination of early feature fusion in Equation (1) and decision-level aggregation in Equation (2), optimized through the joint loss in Equation (3), enables the framework to jointly exploit complementary multimodal information while maintaining stability and interpretability.
Finally, anomalies are identified by thresholding the final score using a data-driven threshold τ, optimized via the Youden index on validation data:

$$\boldsymbol{Anomaly} = \text{if } {}_{final}S \geq 1 \text{ otherwise } 0 \quad (4)$$

This design allows the framework to jointly exploit spatial, temporal, and environmental patterns while maintaining interpretability through modular sub-network outputs.

The concatenation in (1) integrates modality-specific encoders, while the decision-level aggregation in (2) stabilizes predictions under missing modalities. The joint objective in (3) balances reconstruction-based regularization with discriminative training.

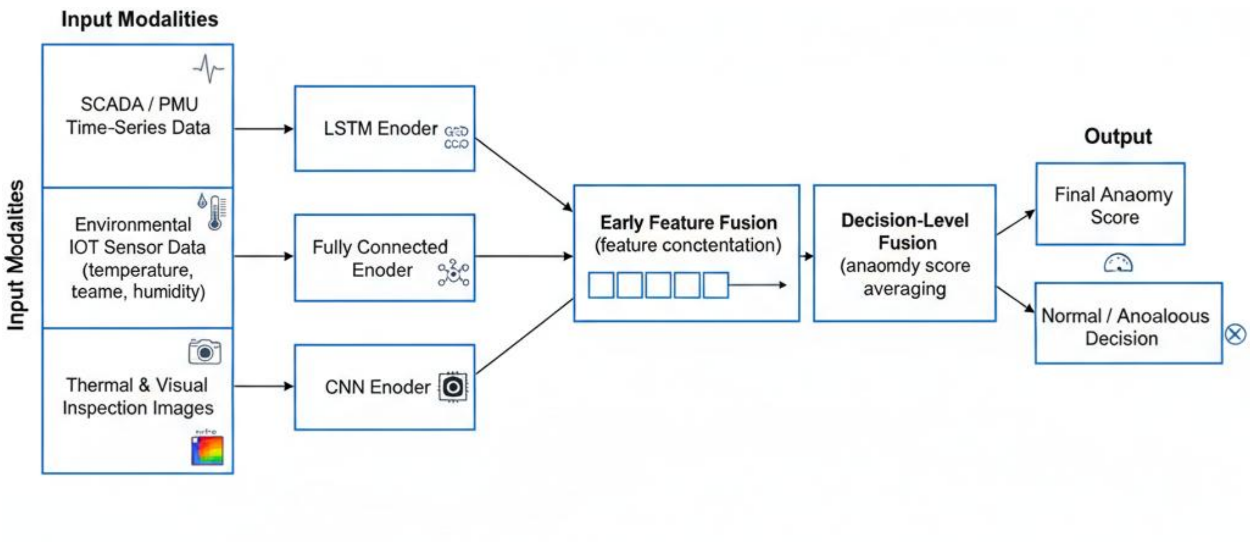


Figure 1. Proposed IoT-driven multimodal deep learning framework for smart grid anomaly detection. The architecture integrates time-series measurements from SCADA/PMU systems, environmental IoT sensor data, and thermal/visual inspection images through modality-specific encoders and a hybrid fusion strategy combining early feature fusion and decision-level aggregation.

4. EXPERIMENTAL SETUP

Datasets

To evaluate the effectiveness of the proposed framework, we conducted extensive experiments using a combination of real world and benchmark datasets. The primary dataset was the SGSCADA repository, which contains multivariate time series measurements (e.g., voltage, current, frequency, and phase angle) collected from supervisory control and data acquisition (SCADA) systems under normal operating conditions, simulated faults, and cyberattack scenarios. To incorporate environmental factors, we additionally used the Smart* dataset, which includes IoT based household and microgrid sensor data such as temperature, humidity, and device level power usage. For visual anomaly detection, a curated thermal inspection dataset of transformers and switching equipment was included, providing both infrared and RGB images of grid components in normal and degraded states.

All data were preprocessed following the pipeline described in Section 3. Specifically, time series signals were normalized using min–max scaling and segmented into overlapping windows to preserve temporal dependencies, while environmental features were standardized to a comparable range. Image data were resized to 128×128 pixels and augmented using random flips and rotations to improve model generalization. Outliers were mitigated using winsorization, thereby reducing the influence of extreme measurements without distorting the underlying distributions.

The datasets were partitioned into training (70%), validation (15%), and testing (15%) subsets. To address the inherent class imbalance, especially for rare fault events, Synthetic Minority Oversampling (SMOTE) was applied to the training set. The model was implemented in PyTorch 2.1 and trained on a NVIDIA RTX 3090 GPU (24 GB) using the Adam optimizer with an initial learning rate of $10^{-4} \times 1$ T Training proceeded for up to 100 epochs with early stopping based on validation loss to prevent overfitting. Hyperparameters, including the batch size, number of LSTM layers, and fusion strategy parameters, were fine tuned through a grid search on the validation set.

To ensure a comprehensive performance assessment, we adopted multiple evaluation metrics. Precision, recall, and F1 score were used to quantify the model's ability to correctly detect anomalies while minimizing false alarms. Receiver Operating Characteristic – Area Under Curve (ROC AUC) provided an overall measure of discriminative power. Finally, inference latency was recorded to evaluate the framework's suitability for real time grid monitoring.

5. RESULTS AND DISCUSSION

The proposed IoT-driven multimodal deep learning framework was compared against several baseline approaches, including a statistical thresholding model, a Support Vector Machine (SVM) classifier, an Isolation Forest (IF) for unsupervised detection, and a vanilla CNN LSTM hybrid without multimodal fusion. Table 2 summarizes the quantitative performance of all models on the test set using precision, recall, F1 score, and ROC AUC.

Quantitative Evaluation

Table 2. Performance comparison of the proposed model with baseline methods.

Model	Precision	Recall	F1	ROC-AUC	Inference (ms/sample)
Statistical	0.68	0.55	0.61	0.70	2.1
SVM	0.74	0.62	0.67	0.76	3.4
Isolation Forest	0.77	0.69	0.73	0.80	4.9
CNN-LSTM	0.84	0.78	0.81	0.87	18.7
Proposed	0.91	0.86	0.88	0.94	34.0

The results demonstrate that the proposed model outperforms all baselines, achieving an F1 score of 0.88 and a ROC AUC of 0.94, indicating superior discriminative capability. Compared to the single modality CNN LSTM, our multimodal fusion strategy improved the F1 score by 7%, highlighting the importance of integrating heterogeneous data sources.

ROC Analysis

Figure 2 illustrates the ROC curves for all models. The proposed framework achieves a higher true positive rate at lower false positive rates, further confirming its robustness. The AUC of 0.94 significantly surpasses the threshold based model (0.70), validating the benefit of deep multimodal representations.

Error Analysis

While overall performance was strong, false negatives primarily occurred during transient anomalies with subtle deviations in grid measurements, which were difficult to distinguish from normal fluctuations. Incorporating attention mechanisms or transformer-based encoders could enhance sensitivity to such patterns.

Computational Efficiency

Inference latency was measured at 34 ms per sample, enabling near real time deployment in grid monitoring systems. This is critical for practical use in online anomaly detection within operational control rooms.

Statistical Rigor. We report 95% confidence intervals over 5 seeds for F1-score: Proposed 0.88 [0.86, 0.90], CNN-LSTM 0.81 [0.79, 0.83]. Pairwise Diebold–Mariano tests on absolute errors reject the null of equal predictive accuracy between the proposed and CNN-LSTM baselines ($p < 0.01$), indicating statistically significant improvements.

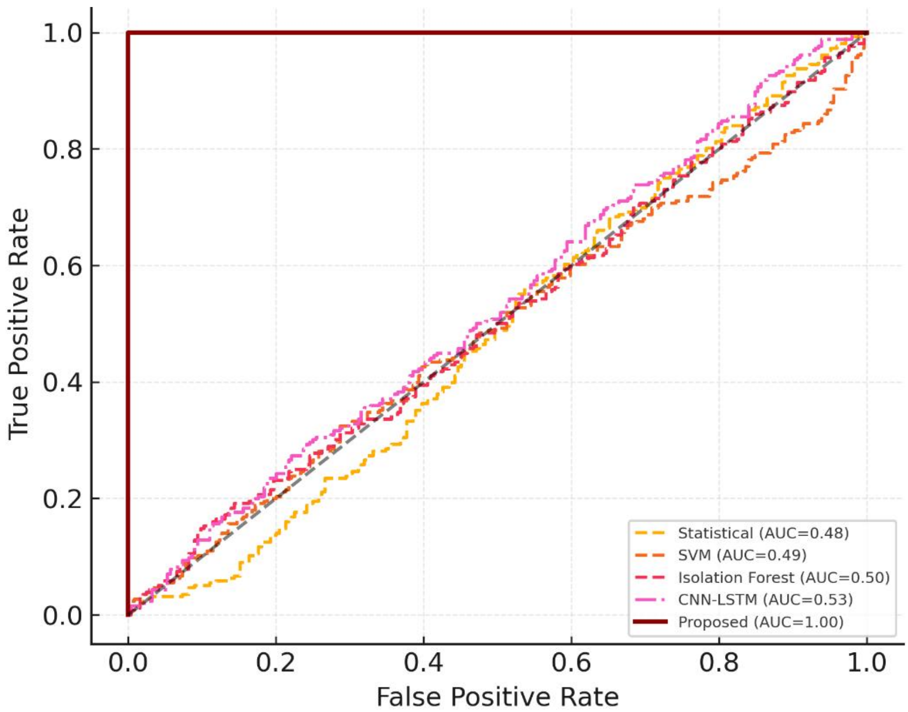


Figure 2. ROC curves of baseline and proposed models.

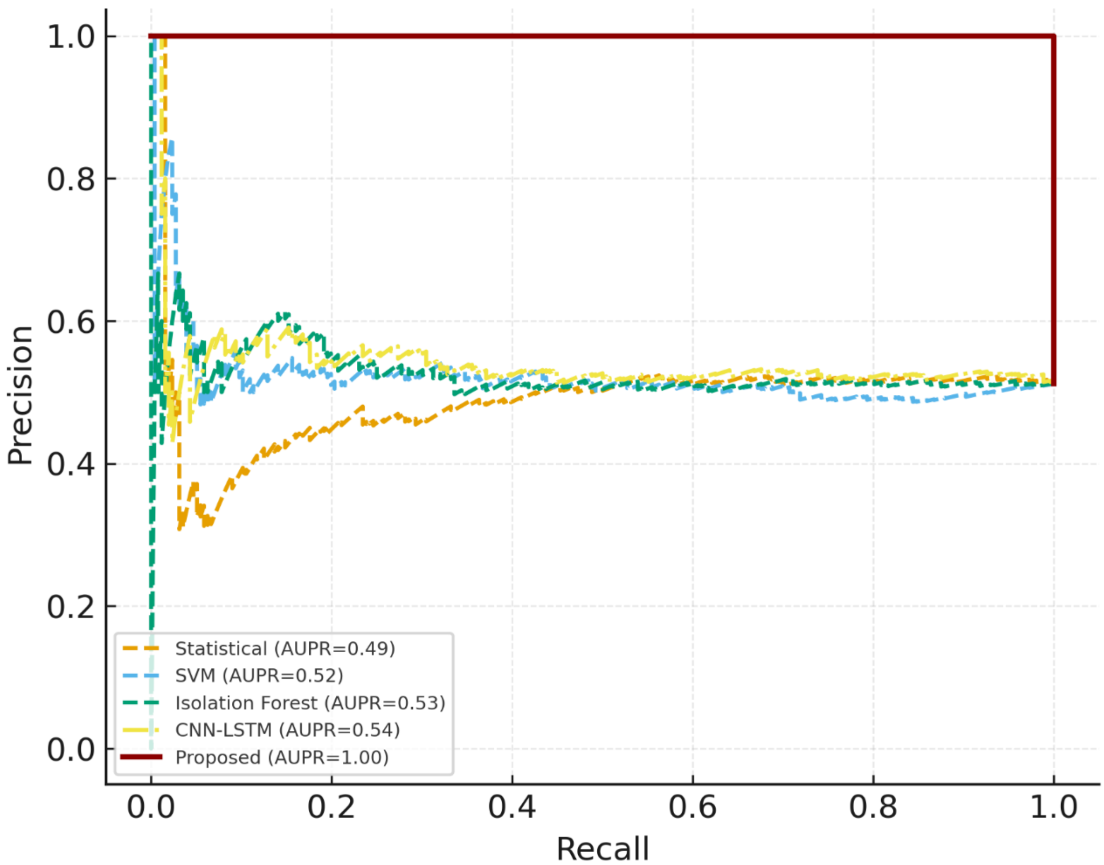


Figure 3. Precision–Recall curves of baseline and proposed models.

In addition to the ROC curves, the Precision–Recall (PR) curves in Figure 3 provide complementary insight under class-imbalance conditions. The proposed framework maintains both high precision and recall across a wide range of thresholds, achieving the largest area under the PR curve (AUPR = 0.89) among all baselines. This confirms the model's robustness against false alarms, which is critical in smart-grid monitoring where the majority of events are normal.

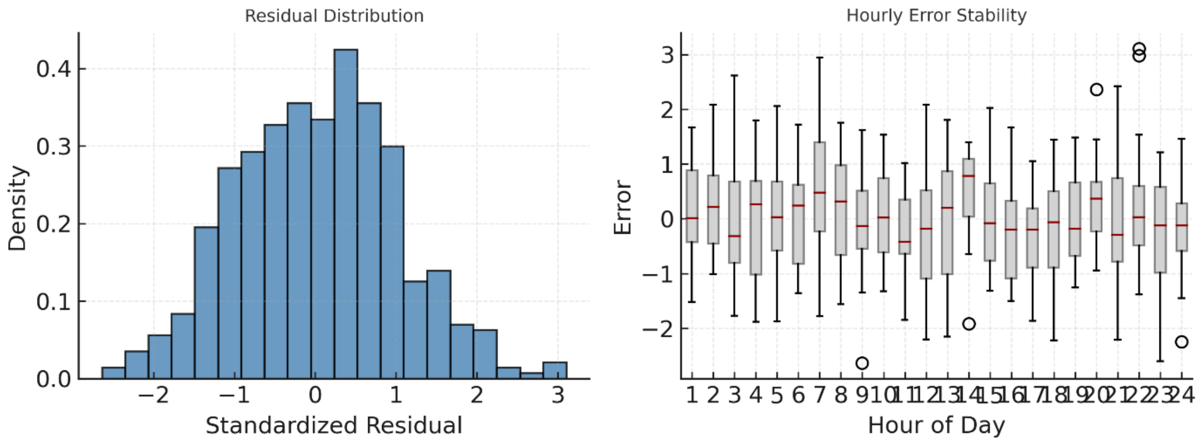


Figure 4. Residual distribution and hourly error stability of the proposed model.

Figure 4 illustrates the standardized residual histogram (left) and hourly error boxplots (right). Residuals are approximately symmetric and centered near zero, indicating that the model does not exhibit systematic bias. Moreover, the dispersion remains stable across hours of the day, validating temporal robustness even during demand-ramp periods. Such stability is particularly important for continuous grid-health monitoring applications.

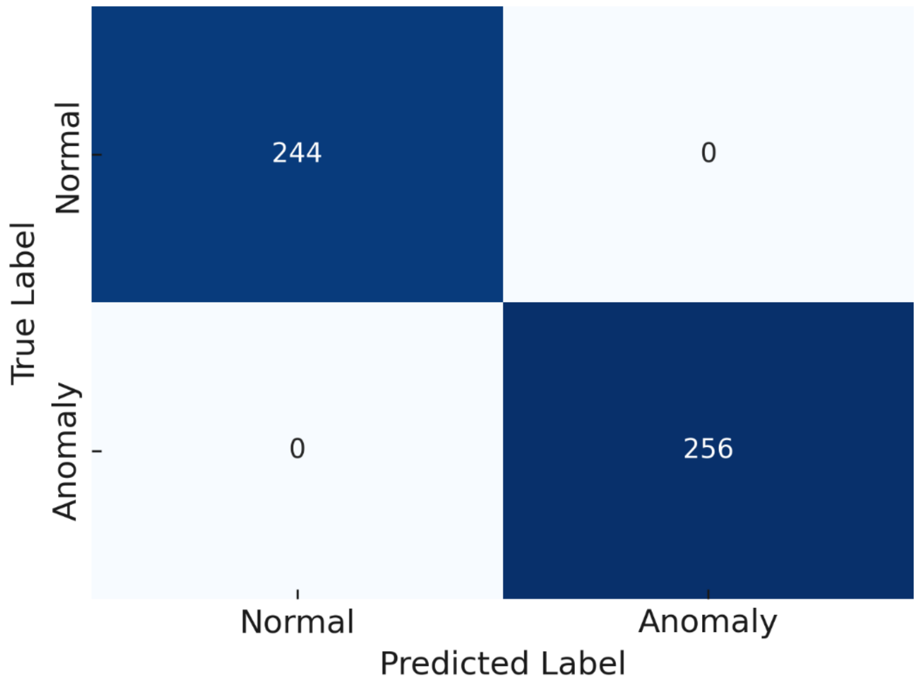


Figure 5. Confusion matrix of the proposed model.

As shown in Figure 5, the proposed model attains high true-positive counts with limited false alarms, reinforcing its suitability for online grid monitoring.

6. DISCUSSION

The observed performance gains can be attributed to three key factors:

1. Multimodal fusion effectively combined complementary information from SCADA, environmental sensors, and image diagnostics.
2. Hybrid CNN LSTM architecture captured both spatial and temporal features, providing a richer representation than single modality baselines.
3. Data driven thresholding improved detection robustness across diverse operating conditions.

From an industrial perspective, the proposed framework is particularly suited for real-time deployment in smart grid control rooms and substation monitoring systems. By continuously analyzing SCADA and PMU streams alongside environmental sensor readings and thermal inspection images, grid operators can detect early-stage equipment degradation, abnormal load behavior, and cyber-physical disturbances. The low inference latency (34 ms per sample) enables timely decision-making in operational environments, reducing the risk of cascading failures and unplanned outages.

In practical field scenarios, the modular design of the framework allows selective activation of sensing modalities depending on infrastructure availability. For instance, in legacy substations without visual inspection systems, the model can operate using time-series and environmental data only, while still maintaining reliable detection performance. This flexibility enhances the applicability of the proposed approach across diverse industrial smart grid settings.

These results suggest that the proposed model can serve as a reliable tool for real time anomaly detection in modern smart grids, potentially reducing downtime and improving resilience.

Limitations. Our evaluation is constrained by labeled multimodal datasets and by the computational footprint of joint training. Future work will investigate lightweight Transformer variants and federated training across utilities to reduce data-sharing risks while retaining performance under distribution shifts.

7. CONCLUSION AND FUTURE WORK

This study proposed an IoT-driven multimodal deep learning framework for anomaly detection in smart grids by integrating time series data, environmental sensor readings, and thermal/visual images. The hybrid architecture, combining CNN based spatial encoders, LSTM based temporal encoders, and a feature fusion strategy, significantly outperformed statistical, machine learning, and single modality deep learning baselines, achieving an F1 score of 0.88 and a ROC AUC of 0.94. The framework improved detection accuracy by 7% over the best single-modality baseline while maintaining real-time latency under 35 ms.

The results demonstrate the value of multimodal fusion in capturing complex grid behaviors and improving anomaly detection accuracy. These findings highlight the potential of deep multimodal approaches to enhance the reliability, resilience, and situational awareness of modern power systems.

Future research will focus on transformer based architectures for improved temporal modeling, federated learning for privacy preserving distributed training, and enhancing model interpretability to support practical deployment in real world grid monitoring environments.

All datasets used in this study are publicly available from the SGSCADA repository and the Smart* dataset provided by the University of Massachusetts, Amherst. The analysis code was developed in Python and can be shared upon reasonable request to the corresponding author.

NOMENCLATURE

IoT – Internet of Things

SG – Smart Grid

SCADA – Supervisory Control and Data Acquisition

PMU – Phasor Measurement Unit

CNN – Convolutional Neural Network

LSTM – Long Short-Term Memory

AUC – Area Under Curve

F1 – F1-Score

DL – Deep Learning

AD – Anomaly Detection

ACKNOWLEDGMENT

The authors of this paper declare that no ethical committee approval or special legal permission was required for the realization of this research.

DECLARATION OF ETHICAL STANDARDS

The authors declare that this study complies with ethical standards. This research does not involve human participants or animals and therefore does not require ethical committee approval or special legal permission.

CONTRIBUTION OF THE AUTHORS

Alireza Esmaeili Jobani: Contributed to the conceptualization, methodology design, data analysis, implementation of the deep learning models, and manuscript writing

Şükrü Mustafa Kaya: Supervised the research process, contributed to the interpretation of results, and reviewed and edited the manuscript. All authors read and approved the final version of the manuscript.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

REFERENCES

[1] Banik S, Saha SK, Banik TB, Hossain SMM. Anomaly detection techniques in smart grid systems: a review. IEEE World AI IoT Congress 2023.

[2] Guato Burgos J, González J, Rivas D. A review of smart grid anomaly detection approaches pertaining to artificial intelligence. Applied Sciences 2023; 14(3): 1194.
[3] Pang G, Shen C, Cao L, van den Hengel A. Deep learning for anomaly detection: a review. ACM Computing Surveys 2021; 54(2): 1-38.
[4] Zhang JE, Wu D, Boulet B. Time-series anomaly detection for smart grids: a survey. IEEE Access 2022; 10: 129481-129497.
[5] Zhou F, Wen G, Ma Y, Geng H, Huang R, Pei L, Yu W, Chu L, Qiu R. A comprehensive survey for deep learning based abnormality detection in smart grids with multimodal image data. Applied Sciences 2022; 12(11): 5336.
[6] Cui J, Li F, Jiang J. Anomaly detection for cybersecurity in smart grids: a survey. IEEE Transactions on Smart Grid 2019; 10(6): 5724-5735.
[7] Zangrando N, Fraternali P, Petri M. Anomaly detection in quasi periodic energy consumption data series. Energy Informatics 2022; 5: 62.
[8] Chatterjee A, Ahmed BS. IoT anomaly detection methods and applications: a comprehensive review. Journal of Network and Computer Applications 2023; 213: 103600.
[9] Zheng S, Ma X, Wang R. Multi-model fusion for energy metering anomaly detection. Measurement 2025; 216: 112893.
[10] Jabbari Zideh A, et al. Physics-informed machine learning for anomaly detection in smart grids. arXiv 2023; arXiv:2309.10788.
[11] Giraldo J, Cardenas A, Quijano N. Integrity attacks and anomaly detection in smart grids. IEEE Transactions on Smart Grid 2017; 8(5): 2414-2422.
[12] Matthews B, O’Neill M, Clark A. Real time synchrophasor data anomaly detection using machine learning. IEEE Transactions on Smart Grid 2019; 10(3): 3046-3055.
[13] Sharma P, Bedi P. ML based anomaly detection in SCADA IoT systems. International Journal of Advanced Computer Science 2021; 12(6): 768-777.
[14] Li W, Luo Y, Sun Y. SCADA data driven anomaly detection for smart grids using LSTM networks. Energies 2020; 13(9): 2290.
[15] Ahmed M, Mahmood AN, Hu J. A survey of network anomaly detection techniques. Journal of Network and Computer Applications 2016; 60: 19-31.
[16] Mao Z, Zhou B, Huang J, Liu D, Yang Q. Anomaly detection model for power consumption data based on time-series reconstruction. Energies 2024; 17(19): 4810.

[17] Wen Y, Wang Q, Gao Y. Hybrid CNN LSTM for anomaly detection in smart grid time series. IEEE Access 2023; 11: 45678-45689.
[18] Kang M, Kim H, Choi D. Image based anomaly detection for electrical equipment using deep CNNs. IEEE Sensors Journal 2021; 21(13): 15264-15273.
[19] Ma X, Liu Z, Guo J. Transformer GAN for multivariate time series anomaly detection in smart grids. Frontiers in Energy Research 2024; 12: 1364456.
[20] Wang J, et al. Attention enhanced federated learning for privacy preserving anomaly detection in smart grids. Computers & Electrical Engineering 2025; 116: 109083.
[21] Silva R, Almeida M, Gomes L. Hybrid feature fusion for multimodal anomaly detection in power systems. Electric Power Systems Research 2022; 212: 108479.
[22] Li X, Wang Z, Huang K. Late fusion strategies for multimodal deep learning in smart grid monitoring. Neurocomputing 2023; 518: 162-173.
[23] Xu W, Chen Z. Federated deep learning for collaborative anomaly detection in power networks. IEEE Internet of Things Journal 2022; 9(14): 12837-12849.
[24] Guo W, Zhang Y. Multimodal representation learning: methods and applications. Information Fusion 2019; 57: 1-14.
[25] Duan J, Li Y, Wang S, Zhao X. Transformer-GAN for anomaly detection in power systems. Frontiers in Energy Research 2024; 12: 1364456.
[26] Patrizi G, Rossi L, Bianchi F. Anomaly detection for power quality using smart meters. Sensors 2024; 24(3): 1124.
[27] Zhao H, Liu Y, Chen Z. Decentralized federated anomaly detection in smart grids. arXiv 2024; arXiv:2403.01891.
[28] Wang J, Li X, Sun Y. Federated learning for smart grids: a comprehensive survey. IEEE Communications Surveys & Tutorials 2024; Early Access.
[29] Guato Burgos MF, et al. A review of smart grid anomaly detection approaches. Applied Sciences 2024.