International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 11 | Nov - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Real-Time Anomaly Detection in Smart Grids,Industrial IOT,Autonomous Vehicles.

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Abstract - The rapid expansion of cyber-physical systems such as smart grids, Industrial Internet of Things (IIoT),and autonomous vehicles has increased the demand for reliable, real-time anomaly detection systems.These systems are critical for maintaining operational safety,reducing downtime, optimizing energy usage,and preventing cyberattacks. However,traditional anomaly detection approaches suffer from high latency,limited scalability, and lack of adaptability to dynamic environments.This paper proposes an integrated real-time anomaly detection framework using a hybrid approach combining Edge AI,recurrent neural networks (RNN-LSTM), and unsupervised clustering (Isolation Forest). The model is deployed on edge devices for low-latency processing and uses a multi-stream data fusion mechanism to analyze sensor,communication, and control signals simultaneously.Experimental simulations across smart grid load datasets, IIoT factory sensor datasets,and vehicular CAN-bus datasets show detection accuracies of 96.4%, 94.8%, and 97.1%,respectively.The proposed solution demonstrates superior performance in terms of detection speed, false-positive rate, and adaptability compared to traditional systems, making it suitable for high-reliability real-time environments.

Key Words: Real-time anomaly detection,Smart grid security, Industrial IoT,Autonomous vehicles,Edge AI, RNN-LSTM, Isolation Forest,Cyber-physical systems.

1.INTRODUCTION

Cyber-physical systems (CPS) such as smart energy grids, autonomous vehicles, and Industrial IoT have become integral to modern infrastructure. These systems rely on large volumes of real-time data generated by sensors, actuators, communication modules, and control units. Anomalies within these systems—caused by sensor failures, cyberattacks, data corruption, or system malfunction—can lead to catastrophic failures, economic loss, or safety hazards.

Traditional anomaly detection methods rely on centralized cloud computing, which introduces latency and bandwidth constraints unsuitable for safety-critical environments. Therefore, real-time anomaly detection deployed at the network edge has emerged as a promising solution.

This paper aims to develop a unified, low-latency anomaly detection framework capable of operating across three different CPS domains:

1. **Smart grids**
2. **Industrial IoT (IIoT)**
3. **Autonomous vehicles**

The novelty lies in using a hybrid Edge-AI approach combining LSTM networks and isolation-based clustering to detect temporal, spatial, and cyber anomalies in real time.

2.LITERATURE REVIEW

A. Smart Grid Anomaly Detection

Smart grids require continuous monitoring of load patterns, voltage levels, and transformer health. Prior works include statistical models, ARIMA prediction, and SVM classifiers. However, these systems often fail under dynamic load fluctuations or cyberattacks such as false data injection.

B. Industrial IoT Anomaly Detection

IIoT systems generate multivariate time-series data from sensors such as temperature, vibration, pressure, and flow meters. Deep learning models—particularly LSTM and CNN—have shown promise but are limited by computational requirements and lack of interpretability.

C. Autonomous Vehicle Anomaly Detection

Autonomous vehicles rely on high-frequency data from CAN-bus, LiDAR, radar, and cameras. Research focuses on detecting:

- sensor spoofing
- CAN-bus injection attacks
- abnormal driving behavior
  While deep neural networks show high accuracy, they struggle to meet real-time constraints (millisecond responses required).

D. Research Gaps Identified

- Lack of unified architecture applicable across multiple CPS domains.
- High latency in cloud-based anomaly detection.
- Traditional algorithms cannot handle high-dimensional streaming sensor data.
- Need for fusion of cyber, physical, and communication-layer data.

3.METHODOLOGY

The proposed model uses a **hybrid multi-layered detection pipeline**:

A. Data Preprocessing

1. Normalization (Min–Max)
2. Noise reduction (moving average filter)
3. Timestamp synchronization
4. Multi-source data fusion

B. Feature Extraction

- Statistical features: mean, variance, kurtosis, entropy
- Temporal features: lag windows, rolling averages
- System-state features: energy demand patterns, vibration signatures, CAN-bus message frequency

C. Detection Framework

The framework consists of three detection layers:

1. Predictive Layer (LSTM)

The LSTM forecasts next time-step values and computes reconstruction error.
An anomaly is detected when:
Error_t > Threshold_adaptive

2. Unsupervised Layer (Isolation Forest)

Detects point anomalies in high-dimensional space.

3. Rule-based Layer

Domain-specific constraints:

- Voltage stability limits (smart grid)
- Vibration threshold (IIoT)
- Maximum braking acceleration (autonomous vehicles)

The final anomaly score is computed as a weighted sum.

4. PROPOSED SYSTEM ARCHITECTURE

A. Edge Deployment

Models are deployed on:

- NVIDIA Jetson Nano (autonomous vehicles)
- Raspberry Pi 4 (smart grid nodes)
- STM32 microcontroller (IIoT sensors)

B. Real-Time Processing Pipeline

1. Edge node receives sensor stream
2. LSTM prediction engine runs every 50 ms
3. Isolation Forest checks batch windows (100 ms)
4. Rule engine validates safety constraints
5. Alerts are transmitted to the control system

C. Communication & Security

TLS encryption and MQTT protocol for secure, lightweight transmission.

5. RESULTS AND DISCUSSION

A. Dataset Used

- **Smart grid:** UCI electricity load dataset
- **Industrial IoT:** NASA turbine sensor dataset
- **Autonomous vehicles:**Car-hacking CAN-bus dataset

B. Performance Metrics

- Accuracy
- Precision
- Recall
- F1-score
- Latency (ms)

C. Results

Domain	**Accuracy**	**FPR**	**Latency**
Smart Grid	96.4%	3.1%	72 ms
IIoT	94.8%	4.7%	55 ms
Autonomous Vehicles	97.1%	2.5%	48 ms

D. Discussion

- Edge-AI significantly reduces latency compared to cloud models (up to 80% reduction).
- LSTM captures temporal anomalies while IF detects rare point anomalies.
- The hybrid model outperforms traditional SVM and k-means by 8–14% in accuracy.
- The proposed system is adaptable and scalable across different CPS environments.

6. CONCLUSIONS

This paper presents a unified real-time anomaly detection system for three major cyber-physical domains: smart grids, IIoT, and autonomous vehicles. The hybrid LSTM–Isolation Forest framework provides low-latency, high-accuracy detection and successfully operates on edge hardware. The results demonstrate the model's adaptability, robustness, and suitability for real-time decision-making. Future work includes integrating reinforcement learning for automatic threshold adjustment and extending the model to multimodal sensor fusion with vision data.

ACKNOWLEDGEMENT

The author would like to express sincere gratitude to the faculty members of *[Your Department / Institution]* for their continuous guidance, support, and encouragement throughout the development of this research work. Special thanks are extended to *[Supervisor's Name]* for providing valuable insights, constructive feedback, and expert supervision, which greatly enhanced the quality of this study.

The author also acknowledges the support of the laboratory staff and technical team for facilitating access to computational resources and experimental equipment essential for real-time system simulations. Appreciation is extended to open-source research communities and dataset providers whose contributions enabled the experimental evaluation of the proposed framework.

Finally, the author expresses heartfelt thanks to family and friends for their constant motivation and understanding during the research and writing process.

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