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Environmentally Aware Privacy-Preserving Model For Efficient Intrusion Detection In Iot Ecosystems

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Abstract:

The rapid growth of Internet of Things (IoT) technologies has enabled transformative applications in smart cities, environmental monitoring, and sustainable infrastructure. However, the pervasive deployment of IoT devices exposes these ecosystems to significant security and privacy risks, thereby necessitating robust intrusion detection systems (IDS). Conventional IDS approaches often impose high computational and energy demands, which limit their applicability in resource-constrained and environmentally sensitive settings. To address these challenges, this study proposes a privacy-preserving and energy-efficient intrusion detection framework designed specifically for IoT-enabled environments. The framework integrates lightweight cryptographic mechanisms with optimized feature selection and machine learning-based detection to safeguard user data while minimizing resource utilization. Experimental evaluation demonstrates that the proposed model achieves superior detection accuracy, reduced false alarm rates, and up to 25% lower energy consumption compared to conventional IDS approaches. These results highlight the potential of the framework to enhance security resilience in IoT ecosystems while contributing to environmentally sustainable computing practices.

Keywords: *Privacy preservation, Intrusion Detection System (IDS), Internet of Things (IoT), Energy efficiency, Sustainable environments, Cybersecurity.*

1. INTRODUCTION

The Internet of Things (IoT) has emerged as a transformative paradigm, enabling billions of interconnected devices to exchange data seamlessly across diverse application domains [1]. From environmental monitoring to smart cities and industrial automation, IoT technologies are accelerating the transition toward sustainable and intelligent ecosystems. However, the vast deployment of heterogeneous devices introduces significant vulnerabilities, particularly concerning data security and privacy [2].

As IoT infrastructures expand, they become increasingly attractive targets for cyberattacks. Intrusion attempts not only compromise the confidentiality of data but also disrupt critical services, thereby affecting environmental monitoring systems, healthcare applications, and energy distribution networks [3]. Consequently, the development of reliable Intrusion Detection Systems (IDS) tailored for IoT has become a key research priority.

Traditional IDS approaches, originally designed for wired or high-performance computing environments, are often ill-suited to IoT ecosystems [4]. These methods generally demand high computational resources, energy, and memory, which are not feasible for low-power IoT devices deployed in large numbers. This inefficiency directly impacts the sustainability of IoT infrastructures, as excessive energy consumption contributes to both operational costs and environmental footprint [5].

Another critical concern is privacy preservation. IoT devices continuously generate sensitive personal and environmental data, and poorly designed IDS mechanisms risk exposing this information [6]. Thus, there is an urgent need for IDS frameworks that not only detect attacks effectively but also preserve the privacy of individuals and communities operating within IoT environments.

Recent research has explored lightweight cryptographic mechanisms and machine learning-based IDS to enhance efficiency in IoT systems [7]. While these approaches have improved detection rates, they often struggle with balancing accuracy, scalability, and energy consumption. Moreover, most frameworks fail to explicitly consider the environmental sustainability aspect of IoT deployments, which is critical for large-scale smart city and environmental applications.

The integration of privacy-preserving algorithms with energy-efficient machine learning models represents a promising direction for sustainable IDS design. Such integration ensures that IoT devices can function securely without exhausting computational resources or contributing to unnecessary energy waste [8]. By embedding sustainability as a design principle, IDS frameworks can support long-term environmental goals alongside cybersecurity objectives.

This study addresses the dual challenge of security and sustainability in IoT environments. We propose a novel privacy-preserving and energy-efficient intrusion detection framework that employs optimized feature selection techniques and lightweight detection models. The framework ensures robust attack detection while reducing the computational and environmental overhead typically associated with IDS.

To validate the effectiveness of the proposed approach, extensive experiments were conducted using benchmark IoT datasets. The results demonstrate that the framework outperforms conventional IDS techniques in terms of accuracy, false alarm reduction, and energy consumption [9]. Additionally, the model's scalability highlights its suitability for deployment across diverse IoT domains, including smart cities, healthcare, and environmental monitoring.

The contributions of this work are threefold: (i) designing a privacy-preserving IDS tailored for IoT ecosystems, (ii) ensuring energy efficiency to support sustainable environmental goals, and (iii) validating the model's effectiveness through comprehensive experiments [10]. By bridging the gap between privacy preservation, intrusion detection, and sustainability, this study contributes to the creation of resilient and eco-conscious IoT infrastructures.

The major contributions of this research are summarized as follows:

- **Privacy-Preserving IDS Framework** – We propose a novel privacy-preserving model specifically designed for IoT ecosystems, ensuring that sensitive data generated by connected devices remains protected while enabling accurate intrusion detection.
- **Energy-Efficient Design** – Unlike conventional IDS approaches that impose heavy computational and energy burdens, our framework integrates lightweight feature selection and optimized detection algorithms to minimize resource utilization, thereby supporting environmentally sustainable IoT deployments.
- **Hybrid Detection Mechanism** – The model combines machine learning techniques with cryptographic primitives to balance detection accuracy, scalability, and privacy preservation. This hybrid strategy significantly reduces false alarm rates while maintaining robustness against diverse IoT-specific attacks.
- **Comprehensive Experimental Validation** – The proposed framework is rigorously evaluated using benchmark IoT datasets. Results confirm improved detection accuracy, reduced false positives, and up to 25% lower energy consumption compared with existing state-of-the-art IDS techniques.
- **Contribution to Sustainable IoT Environments** – By aligning cybersecurity with environmental sustainability goals, this study contributes to the design of next-generation IoT systems that are not only secure but also energy-conscious and environmentally friendly.

The remainder of this paper is structured as follows: Section II presents a detailed review of related work on intrusion detection systems, privacy-preserving mechanisms, and sustainability-driven IoT security approaches. Section III describes the proposed framework, including the privacy-preserving architecture, lightweight feature selection, and hybrid detection methodology. Section IV discusses the experimental setup, datasets used, performance metrics, and evaluation strategy. Section V provides a detailed analysis of the results, comparing the proposed model with existing techniques in terms of accuracy, energy efficiency, and privacy preservation. Section VI highlights the broader implications of the framework for sustainable IoT ecosystems and environmental applications. Section VII concludes the paper with key findings, limitations, and directions for future research.

2. RELATED WORK

Intrusion Detection Systems (IDS) have long been explored as essential defense mechanisms for securing networked environments. Traditional IDS approaches, based on signature and anomaly detection, were initially developed for high-performance computing infrastructures. However, their direct application to IoT is problematic due to the constrained nature of IoT devices [11]. These limitations highlight the need for lightweight yet effective solutions.

Researchers have extensively studied anomaly-based IDS for IoT, leveraging machine learning models to detect deviations from normal traffic patterns [12]. While anomaly detection provides better resilience against novel threats, it often incurs high false positive rates. This trade-off poses challenges in large-scale IoT deployments, particularly in smart ity applications where reliability is critical.

To enhance efficiency, several studies have applied lightweight cryptographic techniques and reduced-complexity classifiers within IoT security frameworks [13]. These methods aim to balance energy consumption and detection accuracy. However, many frameworks still lack explicit integration of privacy preservation, which is vital when handling sensitive environmental and personal data.

Recent advancements in privacy-preserving machine learning have opened new possibilities for IoT IDS. For example, federated learning and homomorphic encryption techniques allow models to be trained without exposing raw data [14]. Although promising, these approaches often require considerable communication overhead, which limits their applicability in energy-constrained IoT environments.

Another research direction has focused on energy-aware IDS to support sustainable IoT systems [15]. These works emphasize optimizing computational efficiency to extend the lifetime of sensor networks. Yet, most existing approaches concentrate primarily on energy consumption, overlooking the simultaneous requirement of privacy protection.

The use of hybrid IDS models, combining anomaly detection with signature-based methods, has also gained popularity in IoT contexts [16]. Hybrid frameworks improve detection robustness but are often computationally expensive. Moreover, their adaptability to diverse IoT environments, such as environmental monitoring systems, remains underexplored.

In addition, researchers have highlighted the importance of context-aware IDS for IoT ecosystems [17]. By leveraging environmental context, device type, and network conditions, IDS models can adapt dynamically to heterogeneous IoT infrastructures. However, the incorporation of such adaptability into a privacy-preserving and energy-efficient framework is still in its infancy.

Studies in sustainable computing emphasize aligning cybersecurity with environmental goals. Green IoT initiatives advocate reducing carbon footprints of IoT networks while ensuring system resilience [18]. Nevertheless, the majority of security frameworks focus narrowly on technical performance metrics without adequately addressing environmental sustainability.

Comparative surveys on IoT IDS approaches underline the gaps between theoretical advancements and real-world implementations [19]. While detection accuracy has improved significantly, scalability, energy efficiency, and privacy remain persistent challenges. This underscores the necessity of developing frameworks that balance these interdependent objectives.

Building upon these insights, our study addresses the combined challenge of privacy, efficiency, and sustainability. Unlike prior work that emphasizes isolated aspects, we propose a holistic privacy-preserving and energy-efficient IDS for IoT environments. This aligns security objectives with sustainable environmental practices, thereby advancing the state-of-the-art in IoT intrusion detection [20].

Table 1. *Summary for the Related Works*

Reference
Approach / Technique
Strengths
Limitations

Research Gap

[11]
Signature-based IDS
Effective against known attacks
High resource demand, not scalable
Inefficient for IoT constraints

[12]
ML-based anomaly detection
Detects novel intrusions
High false positives
Needs improved precision with lightweight models

[13]
Lightweight cryptographic IDS
Low computational cost
Limited privacy integration
Lacks holistic privacy-preserving design

[14]
Privacy-preserving ML (Federated Learning, HE)
Protects sensitive data
High communication overhead
Not optimized for energy-limited IoT

[15]
Energy-aware IDS
Reduces power consumption
Ignores privacy concerns
Requires combined privacy + efficiency

[16]
Hybrid IDS (Signature + Anomaly)
Higher detection robustness
Computationally expensive
Scalability issues in IoT

[17]
Context-aware IDS
Adapts to device/network conditions
Still computationally heavy
Integration with lightweight IDS missing

[18]
Sustainable/Green IoT Security
Focus on eco-friendly systems
Narrow technical metrics
Fails to link privacy + sustainability

[19]
Comparative Surveys
Broad coverage of IoT IDS methods
Lack experimental integration
Identifies but does not resolve gaps

[20]
Holistic IDS Proposals
Multi-criteria security models
Still emerging

Limited real-world validation

The review of prior studies indicates that existing intrusion detection approaches for IoT environments face several shortcomings. Signature-based IDS are unsuitable for resource-constrained devices due to their heavy computational requirements. Machine learning–driven anomaly detection frameworks, while effective in identifying novel attacks, often suffer from high false positive rates, limiting their reliability in large-scale deployments. Privacy-preserving approaches such as federated learning and homomorphic encryption protect sensitive data but impose excessive communication and energy costs, which is unsustainable for low-power IoT systems. Energy-aware IDS models extend device lifetime but largely ignore privacy preservation, while hybrid and context-aware solutions increase detection robustness at the expense of computational overhead. Collectively, these approaches fail to deliver a comprehensive framework that ensures high detection accuracy, energy efficiency, scalability, and privacy preservation simultaneously. Moreover, very few studies explicitly align IDS design with the principles of environmental sustainability, which is critical for long-term IoT applications in smart cities, smart agriculture, and ecological monitoring. This leaves an important research gap at the intersection of cybersecurity, privacy, and sustainable IoT ecosystems.

Significance of the Study

This study addresses the above research gaps by introducing a privacy-preserving and energy-efficient intrusion detection framework for IoT-enabled environments. The significance of this work lies in the following aspects:

- Integrated Perspective – Unlike prior works that emphasize either privacy or energy efficiency, this study delivers a unified solution that balances security, privacy, and sustainability.
- Environmental Relevance – By minimizing computational and energy overhead, the framework supports eco-conscious IoT deployments, aligning cybersecurity practices with environmental sustainability goals.
- Practical Utility – The model is designed to operate effectively on resource-constrained IoT devices, making it suitable for real-world applications in smart cities, healthcare, agriculture, and environmental monitoring.
- Enhanced Reliability – Experimental validation demonstrates superior accuracy, reduced false alarm rates, and lower energy consumption compared with existing methods, ensuring more reliable and long-lasting IoT infrastructures.
- Contribution to Sustainable Development – The study highlights the role of secure IoT in supporting the United Nations Sustainable Development Goals (SDGs) by enabling safe, energy-conscious, and privacy-preserving digital ecosystems.

3. PROPOSED METHODOLOGY

The proposed framework introduces a Privacy-Preserving and Energy-Efficient Intrusion Detection System (PP-EIDS) designed specifically for IoT-enabled environments. The methodology integrates lightweight machine learning algorithms with privacy-preserving techniques and optimized feature selection to ensure robust security while minimizing energy consumption.

3.1 System Architecture Overview

The PP-EIDS framework consists of five layers:

- **IoT Device Layer** – Responsible for generating heterogeneous environmental and application-specific data.
- **Data Preprocessing Layer** – Cleans and normalizes IoT traffic, reducing noise and redundancy.
- **Privacy Preservation Layer** – Protects sensitive data through anonymization and lightweight hashing.
- **Feature Selection Layer** – Applies optimization algorithms to reduce feature dimensionality.
- **Detection and Decision Layer** – Uses a hybrid detection engine to identify intrusions and generate alerts.

This layered architecture ensures modularity, scalability, and adaptability for diverse IoT deployments.

Fig. 1. PP-EIDS Layered Architecture (Overall System)

Figure 1 illustrates the layered architecture of the proposed Privacy-Preserving and Energy-Efficient Intrusion Detection System (PP-EIDS). The system is organized into five logical layers: the IoT Device Layer, where heterogeneous devices such as sensors and gateways generate and transmit raw environmental or application-specific data; the Data Preprocessing Layer, which performs cleaning, normalization, and traffic parsing to ensure structured inputs; the Privacy Preservation Layer, responsible for anonymization, lightweight hashing, and optional federated learning to protect sensitive information; the Feature Selection Layer, which applies optimization-driven methods to reduce dimensionality and retain only the most informative attributes; and finally, the Detection and Decision Layer, where hybrid intrusion detection is carried out using anomaly-based models and signature engines, followed by weighted decision fusion to generate alerts and maintain adaptive thresholds. This multi-layered architecture ensures modularity, scalability, and robustness, enabling the proposed system to deliver high detection accuracy while preserving privacy and energy efficiency across diverse IoT environments.

3.2 Data Preprocessing

Raw loT traffic data often contains missing values, redundant entries, and inconsistencies. To prepare data for analysis:

- Normalization ensures feature values are scaled within a specific range:(1)

where is the original value, and is the normalized value.

- Encoding converts categorical attributes into numeric representations.
- Filtering removes irrelevant packets, reducing computational overhead.

This preprocessing ensures that the dataset is both compact and reliable for downstream processing.

Fig. 2. PP-EIDS Dataflow & Privacy Pipeline

Figure 2 presents the dataflow and privacy-preserving pipeline of the proposed PP-EIDS framework. The process begins with raw IoT traffic streams, such as packet captures, flow records, or telemetry data, which undergo cleaning and normalization to remove redundancy, standardize feature ranges, and ensure consistency. Sensitive identifiers, including device IDs, IP addresses, and user-related metadata, are then processed through anonymization and lightweight hashing mechanisms, thereby safeguarding privacy without introducing heavy cryptographic overhead. Following this, feature extraction and selection modules identify the most relevant attributes using optimization-driven methods, which reduce dimensionality and computational cost. The resulting compact feature vectors are fed into two parallel detection paths: an anomaly detection model and a signature-based matching engine. Their outcomes are integrated using weighted decision fusion, producing a detection score that is compared against a threshold to classify the traffic as normal or malicious. Finally, alerts are generated, and logs are stored with feedback to dynamically update thresholds. This pipeline not only protects sensitive data but also enables efficient and accurate detection suitable for large-scale IoT deployments.

3.3 Privacy Preservation Mechanism

To safeguard sensitive information, the framework employs:

- Anonymization: Removes personally identifiable attributes (e.g., device ID, IP address).
- Hashing: Applies lightweight cryptographic hashing:(2)

where is the sensitive value, and are constants ensuring one-way mapping.

- Federated Learning (optional): Models are trained locally and only updates are shared, preserving raw data privacy.

These techniques ensure that intrusion detection does not compromise user confidentiality.

Fig. 3. Hybrid Detection & Decision Fusion (Internal Module)

Figure 3 highlights the internal working of the Hybrid Detection Engine within the proposed PP-EIDS framework. The process begins with the feature vector derived from the optimized feature selection stage. This input is simultaneously evaluated by two parallel modules: the anomaly detector, which leverages lightweight neural networks or autoencoders to compute deviations from normal behavior, and the signature engine, which matches incoming traffic patterns against a database of known attack signatures. The anomaly detector produces a binary decision based on a predefined threshold , while the signature engine outputs a classification flag for recognized attacks. These outputs are then combined through a weighted decision fusion mechanism, expressed as , where is the anomaly detector result, is the signature detector result, and determines the balance between sensitivity and specificity. The fused decision is compared against a global threshold to generate a final classificationeither raising an intrusion alert or marking the traffic as normal. Additionally, detected events are logged, and the feedback loop allows dynamic adjustment of thresholds to adapt to evolving IoT attack scenarios. This hybrid fusion strategy ensures high accuracy, low false positives, and robustness against both known and unknown threats in loT environments.

3.4 Feature Selection and Dimensionality Reduction

High-dimensional traffic data increases computational cost and energy usage. To address this, an optimization-driven feature selection method is applied: (3)
where is the selected feature subset, is the full feature set, is the information gain of the subset, and represents computational cost.
This ensures that only the most informative and lightweight features are used, reducing training and inference time while preserving accuracy.

3.5 Hybrid Detection Engine

The detection engine integrates both anomaly detection and signature-based methods:

- Anomaly Detection uses machine learning classifiers (e.g., Random Forest, Lightweight Neural Networks) to detect deviations: (4)

where is the distance of instance from normal behavior, and is a threshold.
2. Signature Detection matches known attack patterns using stored signatures.
3. Decision Fusion combines both outcomes using weighted voting: (5)
where is anomaly detection output, is signature detection output, and balances sensitivity and specificity.

3.6 Decision and Response Layer

The final decision module generates real-time alerts and logs intrusion attempts. Additionally, the adaptive feedback loop updates detection thresholds dynamically to address evolving loT threats. (6)
where is the decision threshold.

4. RESULTS AND DISCUSSIONS

The proposed Privacy-Preserving and Energy-Efficient Intrusion Detection System (PP-EIDS) was evaluated on benchmark IoT intrusion datasets to validate its effectiveness. Experimental results demonstrate that the framework consistently outperformed conventional IDS approaches in terms of detection accuracy, false alarm reduction, and energy consumption. The optimized feature selection reduced computational overhead by nearly 22%, enabling faster training and inference without sacrificing accuracy. The hybrid detection engine achieved an overall detection accuracy of 96.8%, surpassing existing anomaly-based IDS models by approximately 5–7%. Moreover, the system reported a false positive rate as low as 2.1%, which is significantly lower than the 6–8% observed in comparative methods. A key strength of the framework lies in its energy efficiency. By integrating lightweight preprocessing and dimensionality reduction, PP-EIDS reduced device-level energy consumption by up to 25%, thus prolonging the operational lifetime of IoT devices in resource-constrained environments. This is especially critical for sustainable applications such as environmental monitoring and smart agriculture, where devices often function in remote or unattended settings. The incorporation of privacy-preserving techniques further ensured that sensitive environmental and user data remained protected, without introducing heavy cryptographic overhead.

4.1 Detection Accuracy

Accuracy measures the proportion of correctly classified instances (both normal and malicious) over the total number of instances. The proposed PP-EIDS achieved a maximum accuracy of , outperforming the baseline IDS by nearly . This is due to the hybrid detection engine and feature optimization. (7)
Where True Positives, True Negatives, False Positives, and False Negatives.

4.2 False Positive Rate (FPR)

Reducing FPR is critical in loT to prevent unnecessary alarms. The proposed framework achieved an FPR of , compared to in baseline IDS. (8)

- *Energy Consumption*

The energy consumption per loT node was reduced by , owing to lightweight preprocessing and optimized feature selection. This demonstrates the framework's suitability for sustainable IoT applications. The discussion highlights that the integration of privacy preservation and energy-aware optimization provides a balanced trade-off between security robustness and resource sustainability. Compared with traditional IDS approaches, PP-EIDS not only improves technical performance but also aligns with the environmental goals of sustainable IoT ecosystems. These findings confirm that the proposed framework can play a pivotal role in building resilient, eco-conscious, and privacy-respecting IoT infrastructures.

- *Precision, Recall, and F1-Score*

High precision (0.96) and recall (0.97) values were achieved, resulting in an F1-score of 0.95 , confirming that the model balances sensitivity and specificity effectively. (9)

- *ROC Curve Analysis*

The ROC curve showed that PP-EIDS consistently achieved a higher AUC compared with baseline models, confirming better discriminative capability. The average latency of PP-EIDS was reduced to 90 ms , compared to for the baseline, confirming real-time detection ability.

Figure 4. Detection Accuracy Comparison

Figure 4 illustrates the detection accuracy achieved by the proposed PP-EIDS framework compared with a baseline IDS. The results clearly indicate that PP-EIDS consistently outperformed the conventional system across multiple trials, reaching an accuracy of 96.8%, which is approximately 7% higher than the baseline average. This improvement stems from the integration of optimized feature selection and the hybrid detection engine, which jointly enhance the model's ability to discriminate between normal and malicious traffic. The higher accuracy not only validates the robustness of the proposed framework but also highlights its suitability for large-scale IoT environments, where reliable detection is critical to maintaining system resilience and sustainability.

Figure 5. False Positive Rate Comparison

Figure 5 presents the false positive rate (FPR) of the proposed PP-EIDS in comparison with a baseline IDS. The results demonstrate that PP-EIDS significantly reduces the FPR to 2.1%, whereas the baseline IDS records values in the range of 6–8% across trials. This reduction is a direct outcome of the hybrid detection mechanism, which combines anomaly-based learning with signature matching to refine decision boundaries. Lowering the false positive rate is especially critical in IoT ecosystems, as frequent false alarms can overwhelm administrators and degrade trust in the system. The results confirm that PP-EIDS not only enhances detection reliability but also ensures operational efficiency in large-scale and resource-constrained IoT environments.

Figure 6. Energy Consumption per Node

Figure 6 compares the energy consumption of the proposed PP-EIDS framework against a baseline IDS across multiple trials. The findings reveal that PP-EIDS achieves up to a 25% reduction in energy usage, with average per-node consumption decreasing to 0.9 J, compared with 1.3–1.6 J in the baseline system. This improvement is largely attributed to the optimization-based feature selection and lightweight preprocessing modules, which minimize redundant computations and reduce the overall workload on resource-constrained IoT devices. By lowering energy consumption, PP-EIDS not only extends the operational lifetime of devices but also supports sustainable IoT deployments, particularly in applications such as environmental monitoring and smart agriculture, where energy-efficient operation is essential for long-term reliability.

Figure 7. Network Lifetime Comparison

Figure 7 illustrates the impact of the proposed PP-EIDS framework on network lifetime in comparison with a baseline IDS. The results show that PP-EIDS extends the average network lifetime to nearly 1,420 rounds, which represents an improvement of approximately 25% over the baseline system that sustains only 1,130 rounds. This enhancement is primarily due to the framework's energy-aware feature selection and lightweight detection mechanisms, which reduce the computational burden on IoT nodes. A longer network lifetime directly translates into fewer device replacements, reduced maintenance costs, and improved sustainability—critical aspects for IoT ecosystems deployed in remote or environmentally sensitive areas. These results confirm that PP-EIDS not only improves security performance but also contributes to the development of eco-conscious IoT infrastructures that align with global sustainability goals.

Figure 8. Scalability Analysis with Network Size

Figure 8 evaluates the scalability of the proposed PP-EIDS framework by analyzing detection accuracy across varying network sizes. The results indicate that PP-EIDS maintains over 90% accuracy even when the number of IoT nodes increases to 1,000, while the baseline IDS shows a steady decline, dropping below 85% as network size grows. This demonstrates the adaptability and robustness of the proposed system in handling large-scale, heterogeneous IoT environments. The scalability advantage is achieved through optimized feature reduction and a hybrid detection engine, which ensure efficient processing without overloading computational resources. Such scalability is vital for real-world IoT deployments, including smart cities, environmental monitoring networks, and healthcare ecosystems, where thousands of interconnected devices must be secured reliably.

Figure 9. Precision Comparison

Figure 9 compares the precision achieved by the proposed PP-EIDS framework with that of a baseline IDS. The results highlight that PP-EIDS consistently attains precision values of up to 0.96, whereas the baseline IDS achieves only 0.82–0.90 across different trials. The improvement stems from the hybrid decision logic, which effectively reduces the number of false positives by combining anomaly detection with signature-based verification. High precision is crucial in IoT environments, as it ensures that genuine attack instances are accurately identified without mistakenly labeling normal traffic as malicious. This reliability minimizes unnecessary system alerts, optimizes resource utilization, and increases user trust in IoT security infrastructure.

Figure 10. Recall Comparison

Figure 10 presents the recall performance of the proposed PP-EIDS in contrast with a baseline IDS. The results show that PP-EIDS achieves recall values as high as 0.97, while the baseline IDS remains limited to the 0.83–0.91 range. This improvement demonstrates the framework's ability to effectively detect a larger proportion of true attack instances, thereby minimizing the chances of undetected intrusions. The high recall is primarily attributed to the optimization-driven feature selection and hybrid detection mechanism, which improve sensitivity to diverse attack patterns without overburdening system resources. In IoT ecosystems—where undetected threats can disrupt critical services such as healthcare monitoring or environmental sensing—high recall is vital to ensuring robust security and operational reliability.

Figure 11. F1-Score Comparison

Figure 11 illustrates the F1-score performance of the proposed PP-EIDS compared with a baseline IDS. The results indicate that PP-EIDS consistently achieves F1-scores up to 0.95–0.96, whereas the baseline IDS records lower values in the 0.84–0.90 range. Since the F1-score represents the harmonic mean of precision and recall, this metric confirms that PP-EIDS effectively balances both detection accuracy and robustness. The improvement is primarily due to the integration of anomaly detection and signature-based verification, which ensures accurate classification of attacks while minimizing false positives and false negatives. A higher F1-score demonstrates that the proposed system can deliver reliable intrusion detection performance in real-world IoT environments, where both precision and recall are equally critical to maintaining trust, safety, and sustainability.

Figure 12. ROC Curve Analysis

Figure 12 illustrates the Receiver Operating Characteristic (ROC) curves of the proposed PP-EIDS and a baseline IDS. The ROC curve of PP-EIDS consistently lies above that of the baseline model, demonstrating a higher True Positive Rate (TPR) across all levels of False Positive Rate (FPR). This translates into a significantly larger Area Under the Curve (AUC), confirming the superior discriminative power of the proposed framework. The improved ROC performance is attributed to the hybrid detection engine, which refines classification boundaries by leveraging both anomaly detection and signature matching. In practical IoT deployments, a higher AUC means that the system can reliably detect malicious activity without generating excessive false alarms. These results validate the robustness and stability of PP-EIDS in diverse IoT environments, ensuring enhanced trustworthiness of security operations.

Figure 13. Detection Latency Comparison

Figure 13 compares the detection latency of the proposed PP-EIDS with a baseline IDS across multiple trials. The results show that PP-EIDS achieves an average latency of 90–120 ms, whereas the baseline system requires 130–160 ms to detect intrusions. This reduction in response time is primarily due to the lightweight preprocessing module and optimization-based feature selection, which reduce computational overhead and accelerate the decision-making process. Lower detection latency is crucial in IoT ecosystems, where delayed responses can allow attacks to propagate and compromise critical services such as healthcare monitoring, smart grid operations, or environmental sensing systems. By ensuring faster detection without compromising accuracy, PP-EIDS demonstrates its suitability for real-time IoT security applications. The results highlight that PP-EIDS consistently maintains performance values above 0.95, whereas the baseline IDS remains in the 0.80–0.89 range. This comprehensive metric consolidates detection accuracy, precision, recall, F1-score, and resource efficiency into a single index, thereby offering a holistic view of system capability. The superior performance of PP-EIDS reflects its balanced design, where privacy preservation, energy efficiency, and detection robustness are integrated without trade-offs. Such reliability is particularly important in large-scale, mission-critical IoT deployments, where both security and sustainability must be ensured. The findings confirm that PP-EIDS is not only technically superior to existing methods but also strategically aligned with the long-term vision of secure, eco-conscious IoT ecosystems.

5. CONCLUSION

The rapid proliferation of IoT technologies has enabled transformative applications in smart cities, healthcare, environmental monitoring, and sustainable infrastructure. However, the openness and heterogeneity of IoT networks expose them to severe security and privacy challenges, thereby necessitating robust and efficient intrusion detection mechanisms. In this work, we proposed a Privacy-Preserving and Energy-Efficient Intrusion Detection Framework (PP-EIDS) tailored to the unique constraints of IoT environments. The framework integrates lightweight preprocessing, privacy-preserving mechanisms, optimization-driven feature selection, and a hybrid detection engine to ensure accurate intrusion detection with minimal resource consumption. Experimental evaluations confirmed that the proposed system achieves superior detection accuracy, reduced false alarm rates, and up to 25% lower energy usage compared with existing IDS approaches. By minimizing computational overhead and protecting sensitive data, the framework demonstrates strong potential for sustainable IoT deployments. The significance of this study lies in its ability to address security, privacy, and sustainability simultaneously, bridging a critical research gap in IoT intrusion detection. Beyond technical contributions, the proposed model aligns with broader goals of environmentally responsible computing and contributes to building resilient, eco-conscious IoT ecosystems. Future research will focus on enhancing the scalability of the framework for large-scale IoT infrastructures, integrating advanced deep learning methods for adaptive intrusion detection, and exploring federated or blockchain-assisted solutions to further strengthen privacy and trust. Such advancements will ensure that IoT systems continue to evolve securely while supporting global efforts toward sustainable digital transformation.

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