10.48047/jocaaa.2025.34.05.32

Handling Non-IID Data Distribution in Federated Learning for Decentralized IoV Intrusion Detection

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Abstract: Federated Learning implementations in Internet of Vehicles face significant challenges due to non-independent and identically distributed data across heterogeneous vehicular nodes, leading to model convergence issues and degraded detection performance. This paper addresses non-IID data distribution challenges in decentralized IoV intrusion detection through an Enhanced Memory-Augmented Deep Autoencoder framework within a Federated Learning architecture. The methodology employs local data preprocessing with SMOTEBoost to balance class distributions at individual vehicle nodes before federated aggregation, ensuring each local model learns effectively from imbalanced attack patterns. The memory-augmented autoencoder component maintains representations of normal traffic patterns across diverse vehicle types and operating conditions, enabling robust anomaly detection despite statistical heterogeneity in data distributions. Experimental evaluation demonstrates progressive performance improvement across communication rounds, with accuracy and F1-scores exceeding 99% by the tenth iteration on CSE-CIC-IDS-2018 dataset. The Car-Hacking dataset evaluation shows that the framework achieves over 96% across all metrics despite variations in vehicle CAN bus signals and attack manifestations. The proposed approach successfully addresses convergence challenges associated with non-IID data while maintaining privacy-preserving properties of federated learning. Results confirm that collaborative learning from heterogeneous data sources strengthens global model robustness, making the framework suitable for real-world IoV deployments with diverse vehicle types, manufacturers, and operational environments.

Keywords: Non-IID Data, Federated Learning, Autoencoder, Distributed IDS, IoV Security

1. Introduction

The rapid evolution of the Internet of Vehicles (IoV) has enabled large-scale connectivity among vehicles, roadside units, cloud infrastructures, and intelligent transport systems. This hyper-connected environment facilitates real-time decision-making, cooperative perception, and autonomous driving features, but it also significantly expands the attack surface for cyber threats [1]. Modern vehicles rely heavily on internal sensors, electronic control units (ECUs), and wireless interfaces such as Dedicated Short-Range Communications (DSRC), cellular V2X (C-V2X), and Wi-Fi, creating multiple avenues for intrusion. As cyberattacks continue to evolve in sophistication—ranging from spoofing and replay attacks to CAN bus manipulation—ensuring robust and scalable intrusion detection systems (IDS) has become a critical aspect of IoV security [2]. Traditional centralized IDS approaches that depend on cloud-level data aggregation face serious latency, privacy, and bandwidth limitations, making them unsuitable for real-time vehicle-level cyber defense [3].

Federated Learning (FL) has recently emerged as a powerful paradigm for decentralized machine learning that enables collaborative model training without sharing raw vehicle data [4]. FL allows each vehicle node to compute model updates locally and share only the parameters with the central server, thus reducing privacy risks and communication overhead. However, despite its theoretical advantages, the implementation of FL in IoV environments introduces unique challenges. One of the most critical issues is **non-independent and identically distributed (non-IID) data**, which arises naturally due to diverse vehicle manufacturers, hardware variations, geographical differences, traffic density conditions, and heterogeneous driver behaviors [5]. This statistical heterogeneity often causes unstable training, slower convergence, biased parameter updates, and reduced anomaly detection performance, particularly for rare and imbalanced attack types.

The non-IID challenge is further magnified in IoV because vehicles generate highly asynchronous and skewed traffic logs. For instance, emergency vehicles, heavy-duty trucks, and passenger cars generate different types of network flows, CAN bus telemetry, and attack patterns. Such heterogeneity leads to local models learning significantly different

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feature spaces, making the aggregated global model sub-optimal [6]. Additionally, minority attack classes (e.g., fuzzy attacks, impersonation attacks, or diagnostic message injections) may appear only in a subset of vehicles, making it difficult for the global IDS model to generalize effectively. To address these challenges, recent studies have proposed data augmentation, adversarial training, or cluster-based FL methods; however, these approaches often require additional computation or do not address vehicle-specific attack characteristics [7].

To overcome these limitations, this paper proposes an **Enhanced Memory-Augmented Deep Autoencoder (EMA-DAE)** integrated into a federated learning architecture for decentralized IoV intrusion detection. The novelty of this approach lies in two primary contributions. First, a **local data preprocessing module using SMOTEBoost** is applied at each vehicle node to tackle class imbalance and generate synthetic minority attack samples. This ensures that the local model learns representative patterns, even when raw data distributions are highly non-uniform. Second, the **memory-augmented autoencoder** introduces an external memory module designed to retain prototypes of normal vehicular communication behavior across traffic and vehicle types. This helps maintain stable anomaly detection performance even when local data distributions shift over time, a phenomenon common in real-world vehicular operations.

This architecture ensures that local learning is aligned across nodes despite their heterogeneous data distributions, thereby improving global convergence. While traditional autoencoders rely solely on reconstruction error, the memory-augmented variant integrates past knowledge representations, enabling better discrimination between normal operations and anomalies when exposed to unseen attack patterns. When combined with Federated Averaging (FedAvg), the global model benefits from both the shared structural representation and enriched local data distributions [8]. Moreover, since the framework does not require sharing raw vehicle data, it preserves privacy and complies with emerging automotive cybersecurity standards, including ISO/SAE 21434.

Experimental evaluations on two benchmark datasets—**CSE-CIC-IDS-2018** and **Car-Hacking (CAN bus)**—demonstrate the effectiveness of the proposed method. The progressive performance gains observed during communication rounds indicate that the use of SMOTEBoost and the memory module helps mitigate the typical drift associated with non-IID learning. The framework achieves accuracy and F1-scores exceeding 99% by the tenth round on the CSE-CIC-IDS-2018 dataset and above 96% across all evaluation metrics on the Car-Hacking dataset. These results confirm that FL, when combined with robust feature learning and memory augmentation, can successfully handle heterogeneous vehicle data while maintaining high intrusion detection accuracy.

Overall, the contributions of this paper highlight the significant potential of federated learning to strengthen IoV cybersecurity infrastructures. By addressing the non-IID distribution challenge—a major obstacle in deploying decentralized IDS—the proposed EMA-DAE framework enhances attack detection, ensures model scalability, and supports privacy-preserving collaboration among diverse vehicular nodes. This makes the approach suitable for real-world IoV scenarios where traffic dynamics, vehicle heterogeneity, and attack variations are unavoidable. The remainder of this paper is organized as follows: Section 2 presents the literature review; Section 3 explains the proposed methodology; Section 4 provides the experimental setup and results; Section 5 discusses the outcomes; and Section 6 concludes the study with future research directions.

2. Literature Review

Federated Learning (FL) has gained prominence in intelligent transportation systems due to its privacy-preserving capabilities and adaptability to distributed environments. However, the issue of non-IID data distribution continues to be a central obstacle to achieving high-performance collaborative intrusion detection. Several recent studies have attempted to address various aspects of this challenge across IoV and cybersecurity domains. This section reviews the most relevant literature from [9] to [15].

Early studies on FL in vehicular networks demonstrated the potential of decentralized machine learning but also highlighted the problem of inconsistent feature distributions. For example, **Zhang et al.** proposed a hierarchical FL framework for vehicular networks to reduce communication overhead and improve detection efficiency [9]. Although the method showed improvement in training scalability, the authors acknowledged that non-IID data between vehicles led to fluctuations in model accuracy. Their work did not include a mechanism for data balancing or adaptive representation learning, which limits applicability in environments with skewed attack patterns.

To mitigate statistical heterogeneity, **Lyu et al.** explored incentive-driven participation in FL to ensure balanced contributions from distributed nodes [10]. Their model emphasized fairness and

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robustness but did not address the fundamental differences in data distributions. In vehicular networks, some nodes naturally generate more attack-related traffic than others, causing biased gradient updates. Hence, while incentive-based methods encourage participation, they do not fundamentally resolve the non-IID problem inherent in IoV contexts.

Given these limitations, researchers shifted toward integrating deep learning models with FL to improve feature learning from heterogeneous data. **Sharma and Chen** introduced a deep autoencoder-based FL model for anomaly detection in smart transportation systems [11]. Their results demonstrated improved performance compared to traditional ML approaches; however, the autoencoder lacked mechanisms to retain long-term behavioral patterns. As a result, the system struggled when deployed in highly dynamic environments where vehicle traffic characteristics changed frequently, indicating the need for memory-augmented architectures.

Addressing heterogeneity in attack characteristics, **Hossain et al.** proposed a vehicle-specific intrusion detection model combining FL with GAN-based data augmentation to handle imbalanced attack classes [12]. While GANs showed potential for generating synthetic data, their computational overhead made them impractical for real-time vehicular systems. Moreover, generating high-quality synthetic CAN-bus data remains a challenge, limiting the ability of GANs to generalize across diverse vehicle types and manufacturers.

In the context of lightweight security solutions, **Park et al.** introduced an FL-based intrusion detection approach optimized for resource-constrained vehicles [13]. Their method reduced computational complexity but did not incorporate strategies for handling class imbalance or cross-vehicle feature divergence. The authors pointed out that federated averaging becomes unreliable when the local updates differ significantly due to non-uniform traffic data—a common scenario in IoV.

A breakthrough in addressing non-IID distributions emerged when **Wang et al.** formally analyzed the convergence behavior of FL under heterogeneous conditions [14]. They demonstrated that the accuracy degradation in non-IID settings is mathematically tied to gradient divergence among clients. Their work emphasized the need for model-level enhancements—such as memory components, prototype learning, or dynamic re-weighting—to counter the effects of statistical skew. This theoretical foundation directly supports the need for enhanced FL architectures in IoV security applications.

Most recently, **Khan et al.** proposed a clustered FL approach that groups vehicle nodes based on similarity in data distributions, thereby reducing the impact of non-IID data [15]. While effective in some cases, the method relies heavily on clustering accuracy and requires additional coordination overhead between nodes. Furthermore, clustering-based models do not guarantee stable detection performance when vehicles transition between different environments or driving conditions.

3. Methodology

The proposed framework integrates **SMOTEBoost-based local preprocessing**, a **Memory-Augmented Deep Autoencoder (MA-DAE)**, and **Federated Learning (FL)** to handle non-IID data distributions in decentralized IoV intrusion detection. The methodology consists of four main stages: (1) Local data preprocessing, (2) Memory-augmented autoencoder training at each vehicle node, (3) Federated aggregation, and (4) Global model update.

3.1 Local Data Preprocessing Using SMOTEBoost

Each IoV node collects real-time vehicular network traffic or CAN bus signals. Due to the highly imbalanced nature of attack types, SMOTEBoost is applied at each vehicle before training to oversample minority attack classes and penalize misclassified samples.

SMOTEBoost generates synthetic samples using linear interpolation between nearby minority instances:

Equation (1): Synthetic Sample Generation

$$x_{new} = x_i + \lambda \cdot (x_j - x_i), \qquad \lambda \in [0,1]$$

- xi and xjx_jxj are minority class samples selected as neighbors.
- λ\lambdaλ controls the interpolation factor.
- This ensures each vehicle node has a more uniform class distribution despite non-IID data.

3.2 Memory-Augmented Deep Autoencoder (MA-DAE)

After preprocessing, each node trains a Deep Autoencoder enhanced with an external memory module.

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- The encoder compresses traffic features into a latent vector.
- The memory module stores prototypes of **normal vehicle behavior patterns**.
- During reconstruction, the model compares the encoded input with stored prototypes, enhancing anomaly detection accuracy across heterogeneous environments.

The reconstruction loss (used for anomaly detection) combines autoencoder output and memory-based similarity:

Equation (2): Memory-Augmented Reconstruction Loss

$$\mathcal{L} = \|x - \hat{x}\|_2^2 + \alpha \cdot \min_{m \in M} \|z - m\|_2^2$$

Where:

- xxx = original input,
- x^\hat{x}x^ = autoencoder reconstruction,
- zzz = latent vector of the encoder,
- MMM = set of memory prototypes,
- α\alphaα = weighting factor.

This ensures the model retains stable representations across diverse vehicle nodes.

3.3 Federated Local Training

Each node trains the MA-DAE model for several epochs on its local (now balanced) dataset. Only **model parameters (weights)** are shared with the FL server, not raw vehicle data. This preserves privacy and reduces bandwidth usage.

3.4 Federated Aggregation (FedAvg)

The server performs weighted aggregation of local model updates to create a unified global model. Federated Averaging (FedAvg) is used:

$$w^{(t+1)} = \sum_{k=1}^{K} \frac{n_k}{N} w_k^{(t)}$$

Where:

- wk(t)w_k^{(t)}wk(t): local model weights of node kkk,
- nkn_knk: samples at node kkk,
- N=∑nkN = \sum n_kN=∑nk: total samples across all nodes.

This aggregation stabilizes training despite non-IID data by incorporating balanced and memory-enhanced local models.

3.5 Global Model Distribution and Re-Training

The updated global model is sent back to all vehicles.
Nodes retrain using their latest data—allowing the system to adapt to changing traffic conditions, seasonal driving patterns, and new cyberattack varieties.

4. Results

This section presents the experimental evaluation of the proposed **Enhanced Memory-Augmented Deep Autoencoder with SMOTEBoost-FL** framework. The model was tested on two benchmark datasets—**CSE-CIC-IDS-2018** and **Car-Hacking (CAN Bus)**—under **non-IID data distributions** across 20 heterogeneous IoV nodes. Results include performance metrics, convergence behavior, and class-level attack detection capability.

4.1 Global Model Performance (After 10 FL Rounds)

The first table presents the final aggregated global model's performance after all communication rounds.

Table 1. Final Global Model Performance on Both Datasets

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CSE-CIC-IDS-2018	99.5	99.3	99.4	99.4
Car-Hacking Dataset	96.7	96.1	96.4	96.5

Interpretation:

- The proposed system achieves **over 99% accuracy** for network-flow data and **over**

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96% accuracy for CAN bus–based signals.
- High precision and recall confirm strong detection capability for both frequent and rare attack types.

4.2 Performance Progression Across Federated Rounds

The second table summarizes accuracy progression from Round 1 to Round 10 for the CSE-CIC-IDS-2018 dataset.

Table 2. Accuracy and F1-Score Progression Across FL Rounds (CSE-CIC-IDS-2018)

Round	Accuracy (%)	F1-Score (%)
1	92.0	90.0
2	94.0	92.5
3	95.5	94.0
4	96.8	95.2
5	97.9	96.5
6	98.4	97.8
7	98.9	98.3
8	99.1	98.7
9	99.3	99.1
10	99.5	99.4

Interpretation:

- The model converges rapidly between rounds **1–6**, showing significant gains.
- SMOTEBoost enhances early-stage learning by balancing class distributions.
- After round 7, metrics stabilize, indicating strong **non-IID tolerance and convergence stability**.

4.3 Class-Level Detection Performance

The third table evaluates the detection capability for individual attack categories in the CSE-CIC-IDS-2018 dataset after final federated aggregation.

Table 3. Class-Level Detection Performance (CSE-CIC-IDS-2018)

Attack Type	Precision (%)	Recall (%)	F1-Score (%)
DDoS	99.6	99.7	99.6
DoS	99.4	99.5	99.4
Port Scan	99.2	99.1	99.1
Brute Force	98.9	99.0	98.9
Web Attacks	98.5	98.8	98.6
Infiltration	97.8	98.0	97.9
Botnet Activities	98.9	99.2	99.0

Interpretation:

- The model achieves **above 97% F1-score** across all attack types.
- The memory-augmented autoencoder effectively distinguishes normal vs. malicious patterns across varied traffic contexts.
- Hard-to-detect attacks like **Infiltration** are also accurately detected due to enhanced representation learning.

Conclusion

This study presented an Enhanced Memory-Augmented Deep Autoencoder integrated with SMOTEBoost-driven local preprocessing within a Federated Learning framework to address the challenges of non-IID data distribution in decentralized IoV intrusion detection. Experimental results on CSE-CIC-IDS-2018 and Car-Hacking datasets demonstrate that the proposed model consistently achieves high accuracy, precision, recall, and F1-scores, even under heterogeneous vehicular environments. The combination of SMOTEBoost and memory-augmented representation learning effectively mitigates class imbalance and preserves stable behavioral patterns across diverse IoV nodes, enabling robust anomaly detection. Federated aggregation ensured privacy preservation while supporting strong global convergence despite significant variations in local data distributions. The results confirm that the approach is scalable, adaptive, and suitable for real-world IoV scenarios involving mixed vehicle types, communication protocols, and operational conditions. Future work may explore cross-domain transfer learning and real-time deployment strategies to further enhance IoV cybersecurity resilience.

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