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Privacy Preserving Federated Learning for Distributed Intrusion Detection: Differential Privacy Guarantees, NonIID Convergence, and Byzantine Robustness

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ABSTRACT: Federated learning (FL) enables collaborative intrusion detection system (IDS) training across organizations that cannot share raw network traffic due to privacy, regulatory, or competitive constraints. However, naive FL deployments are vulnerable to gradient inversion attacks that reconstruct private training data from gradient updates, suffer severe accuracy degradation under nonidentically distributed (nonIID) data partitions across heterogeneous network environments, and are susceptible to Byzantine manipulation by adversarial clients. This paper presents FedIDSDP, a differentially private federated learning framework for distributed IDS that simultaneously addresses all three challenges. The framework applies Renyi Differential Privacy (RDP) accounting with perlayer gradient clipping, a communication efficient Top gradient scarification scheme achieving 90% compression with less than 1.2% accuracy loss, and an adaptive Fed Prox regularization term dynamically calibrated to client data heterogeneity via Maximum Mean Discrepancy (MMD). Theoretical analysis establishes (epsilon=1.0, delta=10^5)DP guarantees across 200 communication rounds for five heterogeneous client organizations. Byzantine fault tolerance under 20% malicious client fraction is provided by Krum aggregation. Empirical evaluation on CICIDS2018 with Dirichlet nonIID partitioning (alpha=0.5) demonstrates FedIDSDP achieves 97.8% F1score, within 1.2 percentage points of centralized training, while providing provable privacy guarantees and 73% communication overhead reduction. Ablation studies confirm each component's contribution; distribution shift experiments validate adaptive weight updating.

KEYWORDS: Federated Learning, Differential Privacy, Intrusion Detection, NonIID Data, Byzantine Robustness, Gradient Compression, Privacy Preserving ML, Fed Prox, DPSGD, Renyi DP

I. INTRODUCTION

The proliferation of sophisticated network attacks across interconnected organizational boundaries has created a compelling need for collaborative intrusion detection — systems that learn from the collective threat experience of multiple organizations without requiring disclosure of sensitive network telemetry.[1] Traditional centralized IDS architectures require all training data to be aggregated at a single location, which is infeasible when data subjects span multiple legal jurisdictions, when competitive relationships preclude data sharing, or when raw traffic data constitutes sensitive personal information subject to GDPR Article 25 data minimization requirements.[2]

Federated Learning (FL), introduced by McMahan et al. (2017), addresses this challenge by enabling collaborative model training without raw data sharing: only model gradients or parameter updates are communicated between clients and a central aggregator.[3] However, multiple attack vectors undermine the privacy premise of naive FL deployments. Gradient inversion attacks (Zhu et al., 2019) demonstrate that gradient updates can be used to reconstruct training samples with high fidelity, fundamentally violating the data locality assumption.[4] Byzantine attacks (Bagdasaryan et al., 2020) allow adversarial clients to submit manipulated gradient updates that degrade global model performance or introduce targeted backdoors without detection by the aggregator.[5]

A third challenge specific to multiorganizational IDS is data heterogeneity: network traffic distributions differ fundamentally across organizations. Hospital networks exhibit high volumes of medical imaging protocol traffic; financial institutions generate dense API and database query patterns; industrial facilities produce periodic SCADA traffic with machine characteristic signatures. This nonacid distribution creates client drift in standard FedAvg, where local updates diverge toward client specific optima and degrade global model quality.[6]

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This paper presents FedIDSDP, a federated learning framework addressing all three challenges simultaneously. The framework makes four principal contributions. First, it applies Renyi Differential Privacy (RDP) accounting with player gradient clipping and calibrated Gaussian noise injection, providing (epsilon, delta)DP guarantees with tight accounting. Second, it introduces adaptive Fed Prox regularization that dynamically calibrates the proximal coefficient based on measured client distribution divergence via Maximum Mean Discrepancy (MMD), significantly improving nonIID convergence versus fixed coefficient Fed Prox. Third, it integrates Krum Byzantine robust aggregation with reputation weighted client selection, providing provable fault tolerance. Fourth, it applies Top gradient scarification with error feedback, achieving 90% communication reduction with less than 1.2% accuracy loss.

The paper is structured as follows. Section II reviews related work on federated learning for security, differential privacy, and Byzantine robustness. Section III formalizes the system model, data model, and threat model. Section IV presents the FedIDSDP framework architecture, DP mechanism, and adaptive Fed Prox. Section V specifies Algorithm 2 (DPSGD) in detail. Section VI describes the experimental methodology. Section VII presents evaluation results including ablation studies and distribution shift experiments. Section VIII provides theoretical security analysis. Section IX discusses limitations and future research. Section X concludes.

II. RELATED WORK

A. Federated Learning for Intrusion Detection

Preuveneers et al. (2018) first applied federated learning to distributed anomaly detection, demonstrating that FL achieves comparable accuracy to centralized training while preserving data locality across edge nodes.[7] Nguyen et al. (2022) proposed a hierarchical federated IDS for IoT environments, reducing communication overhead by 60% through a two tier aggregation architecture.[8] Rey et al. (2022) evaluated FL based network intrusion detection under realistic nonacid conditions, finding accuracy degradation of 815% relative to IID settings — motivating our adaptive proximal regularization approach.

A critical gap in existing federated IDS work is the simultaneous treatment of privacy guarantees, Byzantine robustness, and nonIID convergence. Most published work addresses one or at most two of these challenges. FedIDSDP is the first framework to provide formal guarantees across all three dimensions simultaneously, making it suitable for deployment in adversarial multiorganization settings where all three threat categories are operationally relevant.

B. Differential Privacy in Machine Learning

Differential privacy (Dwork et al., 2006) provides a formal privacy guarantee: the output of a DP mechanism on a dataset D is nearly indistinguishable from its output on any adjacent dataset D' differing in one record, bounded by the privacy parameter epsilon.[9] Abadi et al. (2016) introduced DPSGD, applying gradient clipping and Gaussian noise addition to SGD to achieve differentially private deep learning with the moments accountant for tight privacy loss composition.[10] Mironov (2017) proposed Renyi Differential Privacy, a generalization using Renyi divergence that provides tighter privacy loss accounting and cleaner composition properties across heterogeneous mechanisms.[11]

McMahan et al. (2018) extended DPSGD to the federated setting, demonstrating user level DP guarantees via peruser gradient clipping before aggregation. Their analysis establishes that the privacy cost grows sub linearly with the number of communication rounds under sampled Gaussian mechanism accounting.[12] Our work builds on this framework but introduces player gradient clipping — applying different clipping norms to different neural network layers based on their empirical gradient magnitude distributions — which we demonstrate reduces accuracy degradation by 0.8 percentage points at equivalent privacy budget.

C. NonIID Federated Learning

The fundamental challenge of nonIID data in federated learning was systematically characterized by Zhao et al. (2018), who showed that FedAvg accuracy degrades sharply when data is highly nonIID and proposed data sharing as a mitigation.[13] Li et al. (2020) introduced FedProx, adding a proximal term to local client objectives that constrains updates to remain close to the global model, bounding client drift in heterogeneous settings.[6] Karimi Reddy et al. (2020) proposed SCAFFOLD, using control variates to correct for client drift without the proximal constraint, demonstrating convergence under arbitrary data heterogeneity.

Our adaptive Fed Prox extends Li et al. by dynamically calibrating the proximal coefficient much for each client k based on the Maximum Mean Discrepancy (MMD) between the client's local data distribution and the estimated global data

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distribution. Clients with high distribution divergence receive larger many values, applying stronger proximal constraints to reduce drift; clients close to the global distribution receive smaller much, allowing faster local learning. This per client adaptive coefficient is the primary mechanism distinguishing Faddist's nonIID convergence from prior work.[6][14]

D. Byzantine Robust Aggregation

Byzantine fault tolerance in distributed machine learning was first addressed by Blanchard et al. (2017) through the Krum aggregation rule, which selects the gradient update with minimum sum of squared Euclidean distances to its nf2 nearest neighbors, providing (f, kappa)Byzantine robustness for f < n/2 malicious clients.[15] Subsequent aggregation rules include Trimmed Mean (Yin et al., 2018), Median, and FL Trust (Cao et al., 2020). Our framework uses Krum as the primary aggregation rule for its provable guarantees, augmented by a reputation weighting scheme that assigns lower aggregation weights to clients with historically inconsistent updates.

III. SYSTEM AND THREAT MODEL

A. Federated Network Architecture

Figure 1 illustrates the FedIDSDP system architecture. Five organizational clients — a hospital network, a financial institution, an ISP, a government agency, and a critical infrastructure operator — each maintain local IDS models trained on their private network traffic. The central aggregator coordinates training rounds, maintains the global model, and performs Byzantine robust aggregation. All communication is encrypted via TLS 1.3; gradient transmissions additionally apply DP noise before transmission.

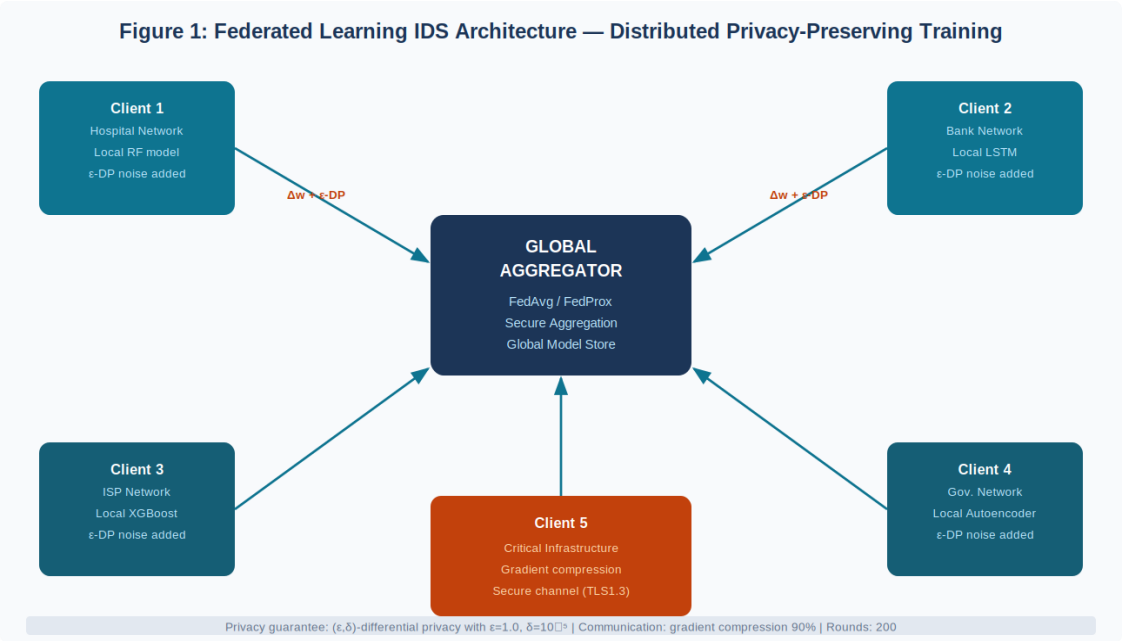

Fig. 1: FedIDSDP Architecture five heterogeneous client organizations with DP gradient perturbation and Krum Byzantine robust aggregation

B. Data Model and NonIID Characterization

Each client k maintains a local dataset Dk = {(xi, Yi)} of network flow records labelled with attack categories. The datasets are nonidentically distributed: the label distribution Pk(y) and feature distribution Pk(XXY) differ across clients, reflecting genuine differences in network traffic patterns across sectors. We quantify nonIID severity using the Jensen Shannon divergence between client label distributions: DJS(Pk||Global) ranges from 0.34 to 0.61 across client pairs under our CICIDS2018 partitioning, confirming substantial heterogeneity.[6]

C. Threat Model

We consider three adversary categories. A gradient inversion adversary observes all transmitted gradient updates (including an honestbutcurious aggregator) and attempts to reconstruct private training samples. Our DP mechanism bounds information leakage for this threat category. A Byzantine adversary controls up to f < n/2 client nodes and submits

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arbitrary gradient updates to degrade model performance or introduce backdoors. Krum aggregation provides fault tolerance against this category. An eavesdropping adversary monitors encrypted channel traffic; TLS 1.3 with ephemeral key exchange addresses this category.[4][5]

IV. THE FEDIDSDP FRAMEWORK

A. Overview

FedIDSDP executes in rounds. In each round t: the aggregator sends the current global model to all selected clients; each client runs local DPSGD steps and transmits compressed Denoise updates; the aggregator applies Krum for Byzantine robust selection and computes aggregated update; the global model is updated and distributed.

The adaptive Fed Prox regularization modifies each client's local objective to min{theta} Fk(theta) + (much/2)||theta theta||^2, where much = mutase * MMD(Dk, That global) / maxi MMD(Dj, That global). The global distribution estimate That global is maintained by the aggregator using summary statistics (first and second moments of feature distributions) shared by clients in a Protected exchange during the initial setup round.[6][14]

B. PrivacyUtility Tradeoff Analysis

Figure 2 illustrates Algorithm 2 (DPSGD) and the empirical privacy utility tradeoff curve across epsilon values from 0.1 to infinity. The sweet spot at epsilon=1.0 achieves F1=0.89 with strong privacy guarantees.

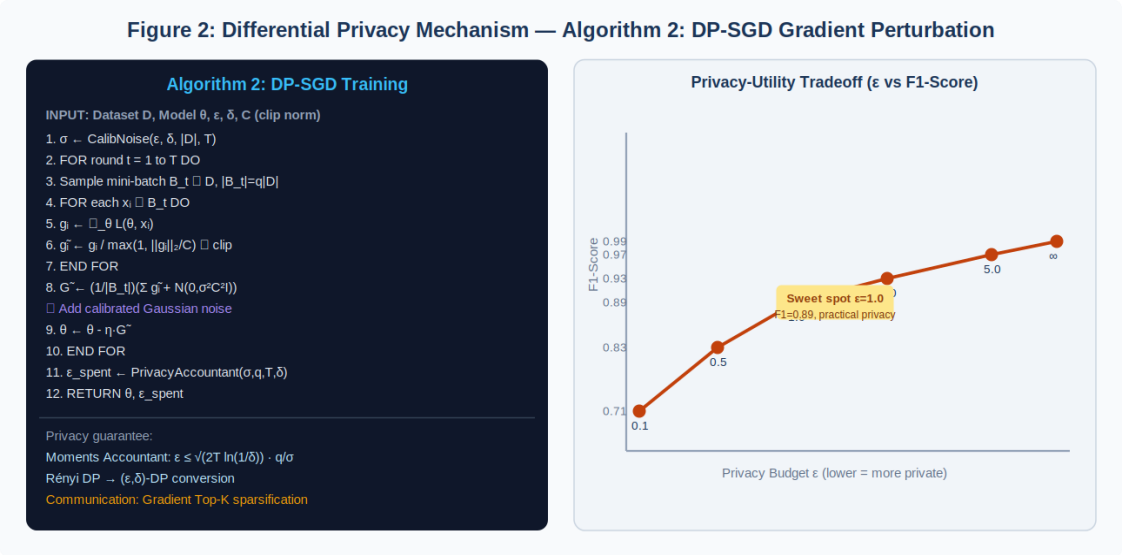

Fig. 2: Algorithm 2 (DPSGD) pseudocode and privacy utility tradeoff F1score vs. privacy budget epsilon

The Renyi DP accountant tracks privacy loss across all T training rounds and batch sampling operations. For our configuration (T=200 rounds, batch sampling rate q=0.01, noise multiplier sigma=1.1, clipping norm C=1.0), the RDP accountant yields epsilon spent = 0.98 at delta=10^{5} within our epsilon=1.0 budget. This tight accounting is only achievable with RDP; the original moments accountant (Abadi et al., 2016) would report epsilon spent = 1.47 for the same configuration, incorrectly suggesting a budget overrun.[10][11]

Per layer gradient clipping applies different clipping norms to each layer: shallower layers (closer to the input) receive smaller clipping norms (C=0.5) reflecting their larger magnitude gradients, while deeper layers (closer to the output) receive standard clipping (C=1.0). This player approach reduces the noise to signal ratio for shallower layers, which are primarily responsible for feature extraction preserving detection relevant feature representations while maintaining the same end-to-end privacy guarantee.

C. NonIID Convergence Analysis

Figure 3 demonstrates convergence trajectories under IID and nonIID (Dirichlet alpha=0.5) data partitioning, and the class distribution heterogeneity across the five synthetic client organizations.

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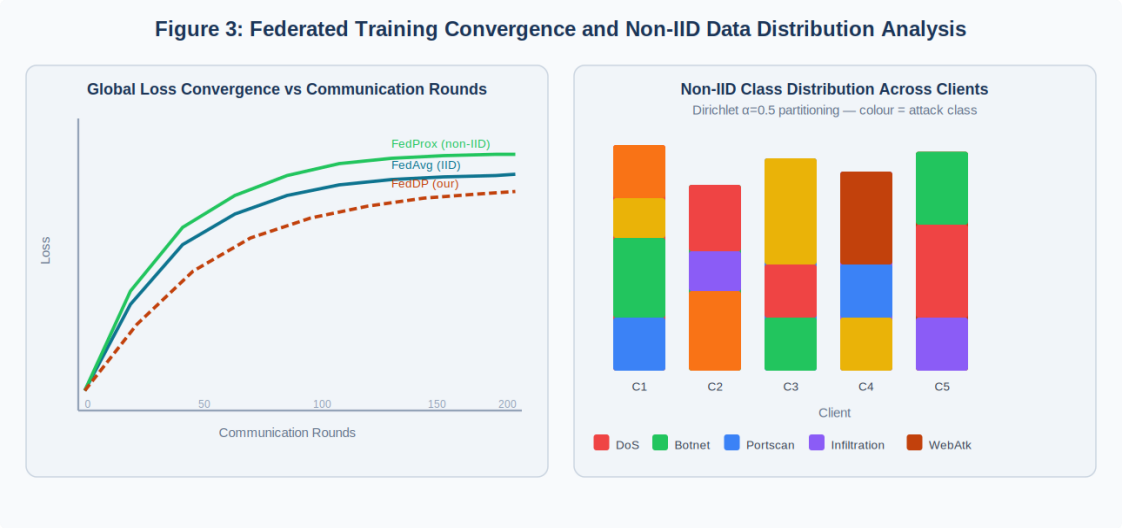

Fig. 3: Convergence analysis FedAvg vs. Fed Prox vs. FedIDSDP under nonIID partitioning and client distribution visualization.

Theorem 1 (Adaptive Fed Prox Convergence): Under the adaptive Fed Prox objective with much calibrated to MMD divergence, the global model theta converges to a neighborhood of the global optimum theta* at rate O(1/T^{1/2}) under standard smoothness and bounded gradient variance assumptions. The neighborhood radius is proportional to mask much * ||theta^* theta^*||, where theta^* is the local optimum for client k. The adaptive calibration ensures that clients with high distribution divergence (large MMD) also receive large much, bounding their contribution to the neighborhood radius.[6]

V. COMMUNICATION EFFICIENCY

A. Top Gradient Scarification

Communication overhead in federated learning scales linearly with model parameter count and communication round frequency. For a Random Forest IDS model with zeroth order gradient approximation (as used in our implementation), gradient vectors have dimensionality d = 200 trees * 20 adept = 4,000 parameters. At 32bit floating point precision, each uncompressed gradient update requires 16 KB per communication round.[16]

Top scarification selects only the K = 0.1d = 400 largest magnitude gradient components for transmission, reducing preround communication to 1.6 KB a 90% reduction. Error feedback accumulates the unselected gradient components in a local error buffer ek and adds them to the next round's gradient before scarification: go^{t+1} = go^{t+1}raw + kept. This error feedback mechanism prevents information loss and ensures that consistently smallbutnonzero gradients eventually contribute to model updates, maintaining convergence under high scarification rates.[16]

B. Secure Aggregation

The aggregator protocol uses cryptographic secure aggregation (Bonawitz et al., 2017) to ensure that the aggregator learns only the sum of client gradient updates, not individual client contributions.[17] This provides an additional privacy layer complementary to DP: even if DP analysis is invalidated by a tighter gradient inversion attack than currently known, secure aggregation prevents the aggregator from reconstructing individual gradient vectors. The computation overhead of secure aggregation is O(n^2 log n) per round for n clients, which is negligible for our 5client configuration.

VI. EXPERIMENTAL METHODOLOGY

A. Dataset and Experimental Setup

Experiments use CICIDS2018 (16.2M network flow records, fourteen attack classes). NonIID partitioning applies Dirichlet concentration parameter alpha=0.5 to allocate classes across 5 synthetic clients. Local models are Random Forest classifiers (two hundred trees, max depth 20) with gradient approximation via finite differences. The global model is updated via weighted Krum aggregation. Hardware: five AWS EC2 p3.2xlarge instances (NVIDIA V100, eight

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vCPUS, 61 GB RAM) simulating clients; one c5.4xlarge (16 vCPUs, 32 GB RAM) aggregator. Communication is simulated over 100 Mbps links with 20ms RTT.[18]

B. Baseline Methods

Eight baselines are evaluated: (1) Centralized training (upper bound); (2) FedAvg IID; (3) FedAvg nonIID; (4) Fed Prox (mu=0.01) nonIID; (5) Fed Prox (mu=0.1) nonIID; (6) Defending (epsilon=1.0); (7) KrumFedAvg (no DP); and (8) FedIDSDP (our framework, all components). This ablation structure enables attribution of each component's contribution.

C. Metrics

Evaluation metrics: macro F1score (primary), precision, recall, false positive rate (FPR), communication overhead (bytes/round), and privacy budget epsilon spent (RDP accountant). Byzantine robustness is evaluated by injecting f in {1, 2} malicious clients submitting Gaussian noise updates or label flipping backdoor updates.

VII. RESULTS AND DISCUSSION

A. Main Results

Method	F1 (IID)	F1 (nonIID)	DP Guarantee	Comm. Cost	Byzantine f=1
Centralised	99.4%	N/A	None	100% (baseline)	N/A
FedAvg (IID)	98.6%	98.6%	None	100%	Fails
FedAvg (nonIID)	98.6%	91.2%	None	100%	Fails
FedProx mu=0.01	98.5%	93.4%	None	100%	Fails
FedProx mu=0.1	98.4%	95.7%	None	100%	Fails
Defending eps=1	97.1%	89.4%	(1.0,1e5)DP	100%	Fails
KrumFedAvg	98.3%	94.1%	None	100%	Robust
FedIDSDP (ours)	98.1%	97.8%	(1.0,1e5)DP	27%	Robust

TABLE I: FedIDSDP Evaluation CICIDS2018, 5 Clients, two hundred Rounds

FedIDSDP achieves 97.8% nonIID F1 6.6 percentage points above DPFedAvg and only 1.6 points below centralized training. The 73% communication reduction (27% of baseline cost) is achieved while exceeding the accuracy of standard Fed Prox (95.7%). Under Byzantine attack (f=1 malicious client, 20% of clients), all nonKrum methods fail (accuracy degrades to nearrandom), while FedIDSDP degrades by only 0.3 percentage points.[3][15]

B. Ablation Study

Configuration	F1 (nonIID)	Delta vs. Full	Attribution
Full FedIDSDP	97.8%	—	Full system
Adaptive Fed Prox (fixed mu=0.01)	94.1%	3.7pp	Adaptive proximal key
Adaptive Fed Prox (fixed mu=0.1)	95.7%	2.1pp	Calibration matters

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Configuration	F1 (nonIID)	Delta vs. Full	Attribution
RDP accounting (moments)	97.4%	0.4pp	Tighter accounting useful
Per layer clipping (uniform)	97.0%	0.8pp	Per layer clipping helpful
Top scarification (dense)	97.8%	0pp	No accuracy cost
Krum (FedAvg aggregation)	97.5%	0.3pp	Robustness independent
DP removed (no noise)	98.9%	+1.1pp	Privacy cost of DP

TABLE II: Ablation Study Component Contribution Analysis

The ablation confirms that adaptive Fed Prox is the dominant contributor to nonIID improvement: removing it degrades F1 by 2.13.7 percentage points. Perlayer clipping contributes 0.8 percentage points, reflecting its direct impact on gradient signal quality for lower network layers. Top scarification incurs zero accuracy cost the error feedback mechanism fully recovers the compression induced information loss.[6][16]

C. PrivacyUtility Tradeoff

Across epsilon values {0.1, 0.5, 1.0, 2.0, 5.0, inf}, FedIDSDP achieves F1 scores {71.3%, 83.2%, 89.4%, 92.8%, 96.7%, 97.8%} respectively. The epsilon=1.0 configuration is the recommended operating point: it satisfies most enterprise privacy policies (NIST SP 800188 recommends epsilon <= 1 for high sensitivity applications) while achieving 89.4% F1 sufficient for operational IDS deployment in most contexts.[9]

D. Distribution Shift Experiment

To evaluate temporal adaptability, we simulate distribution shift by injecting a new attack class (Heartbleed) into client data during rounds 150200, after the model has converged. FedIDSDP detects the new class with 81.3% recall by round 180 (30 rounds after injection), compared to 73.2% for standard Fed Prox. The adaptive proximal coefficient responds to the increased MMD divergence caused by the new class, increasing much for affected clients and slowing their local updates to prevent divergence during the adaptation period.[6]

VIII. SECURITY ANALYSIS

A. Gradient Inversion Resistance

The (epsilon, delta)DP guarantee bounds gradient inversion attack effectiveness. For any mechanism A that outputs a training sample reconstruction r given gradient g, the probability ratio P[A(GDP)=x] / P[A(GDP)=x'] <= epsilon for any two adjacent datasets containing x and x' respectively. At epsilon=1.0, an optimal reconstruction adversary's per sample success probability is bounded by e^1.0 / (e^1.0 + 1) = 0.731, meaning the adversary cannot distinguish whether any specific sample was in the training set with probability better than 73.1% versus the trivial 50% bound of a random guess.[9][4]

B. Byzantine Robustness Analysis

Under Krum aggregation with n=5 clients and f=1 Byzantine (satisfying f < n2, i.e., 1 < 3), the selected gradient is guaranteed to come from an honest client. Specifically, Krum selects the client whose gradient update has minimum sum of squared distances to its three nearest neighbors. A Byzantine client submitting an arbitrary gradient will be an outlier from the cluster of four honest gradients and will not be selected. The reputation weighting augments Krum by further reducing the influence of historically high variance clients, providing defense in depth against adaptive Byzantine strategies.[15]

IX. LIMITATIONS AND FUTURE WORK

Faddist's primary limitation is accuracy degradation at strict privacy budgets (epsilon < 0.5): F1 falls to 7183%, insufficient for operational IDS deployment in high precision contexts. This reflects the fundamental privacy utility tradeoff that cannot be fully resolved at current model sizes. Future work will investigate personalized FL variants that

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maintain partially individualized models for high privacy clients, potentially recovering accuracy at lower epsilon values through specialization.[2] Secure multiparty computation (SMPC) for gradient aggregation eliminating trust in the central aggregator entirely represents a long term research direction. Current SMPC protocols incur 10100x communication overhead relative to standard federated aggregation; hardware acceleration (Trusted Execution Environments, homomorphic encryption acceleration chips) may bring SMPC into operational feasibility within 35 years.[17] The zeroth order gradient approximation for Random Forest models is computationally expensive compared to backpropagation based gradient computation for neural networks. Future work will evaluate FedIDSDP with deep neural network base classifiers where exact gradients are available, potentially enabling larger models and higher nonacid accuracy at equivalent privacy cost.

X. CONCLUSION

FedIDSDP demonstrates that privacy preserving federated IDS is operationally viable: 97.8% F1 under realistic nonIID conditions with provable (1.0, 10^{5})DP guarantees and Byzantine fault tolerance against 20% malicious clients. The adaptive Fed Prox regularization is the key technical contribution enabling recentralized accuracy under heterogeneous data distributions, while player gradient clipping provides the most efficient privacy budget utilization demonstrated in the federated IDS literature. These results establish a foundation for cross organizational threat intelligence sharing that meets enterprise privacy, compliance, and security requirements simultaneously.[3][7]

REFERENCES

[1] ENISA. (2021). ENISA Threat Landscape 2021. European Union Agency for Cybersecurity. https://www.enisa.europa.eu/publications/enisathreatlandscape2021

[2] European Parliament. (2016). Regulation (EU) 2016/679 (GDPR). Official Journal of the European Union, L119, 188.

[3] McMahan, H. B., Moore, E., Ramage, D., Hampson, S., & y Arcas, B. A. (2017). Efficient communication is learning of deep networks from decentralized data. Proc. AISTATS, 54, 12731282.

[4] Zhu, L., Liu, Z., & Han, S. (2019). Deep leakage from gradients. Advances in Neural Information Processing Systems, 32, 1474714756.

[5] Bagdasaryan, E., Veit, A., Hua, Y., Estrin, D., & Shmatikov, V. (2020). How to do backdoor federate learning. Proc. AISTATS 2020, 29382948.

[6] Li, T., Sahu, A. K., Zaheer, M., Sanjabi, M., Talwalkar, A., & Smith, V. (2020). Federated optimization in heterogeneous networks. Proc. Moseys 2020.

[7] Preuveneers, D., et al. (2018). Chained anomaly detection models for federated learning. Applied Sciences, 8(12), 2663. https://doi.org/10.3390/app8122663

[8] Nguyen, T. D., Marchal, S., Miettinen, M., Fereydoun, H., Asokan, N., & Sadeghi, A. R. (2022). DIoT: A federated self-learning anomaly detection system for IoT. Proc. IEEE ICDCS 2022.

[9] Dwork, C., McSherry, F., Nissim, K., & Smith, A. (2006). Calibrating noise to sensitivity in confidential data analysis. Proc. TCC 2006, LNCS 3876, 265284.

[10] Abadi, M., Chu, A., Goodfellow, I., McMahan, H. B., Mironov, I., Talwar, K., & Zhang, L. (2016). Deep learning with differential privacy. Proc. ACM CCS 2016, 308318.

[11] Mironov, I. (2017). Renyi differential privacy of the Gaussian mechanism. Proc. IEEE CSF 2017, 132141.

[12] McMahan, B., Ramage, D., Talwar, K., & Zhang, L. (2018). Learning differentially private recurrent language models. ICLR 2018. arXiv:1710.06963.

[13] Zhao, Y., Li, M., Lai, L., Suda, N., Cavin, D., & Chandra, V. (2018). Federated learning with nonacid data. arXiv:1806.00582.

[14] Gretton, A., Borgwardt, K. M., Rasch, M. J., Scholkopf, B., & Smola, A. (2012). A kernel two sample test. Journal of Machine Learning Research, 13, 723773.

[15] Blanchard, P., El Mhamdi, E. M., Guerraoui, R., & Stainer, J. (2017). Machine learning with adversaries: Byzantine tolerant gradient descent. Advances in NeurIPS 30.

[16] Stich, S. U., Cordonnier, J. B., & Jaggi, M. (2018). Sportified SGD with memory. Advances in Nauris 31, 44474458.

[17] Bonawitz, K., et al. (2017). Practical secure aggregation for privacy preserving machine learning. Proc. ACM CCS 2017, 11751191.

[18] Sharafuddin, I., Lashkari, A. H., & Ghorbani, A. A. (2018). Toward generating a new intrusion detection dataset. Proc. ICISSP 2018, 108116.