Cloud Intrusion Detection System Using Co–Operative Machine Learning Technique

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***Abstract*—Traditional Intrusion Detection Systems (IDS) rely on centralized data structures. This creates major risks for user privacy, leads to significant communication bandwidth issues, and poses single-point-of-failure (SPOF) threats. Additionally, real-world network traffic data often suffers from extreme class imbalance. This skews conventional machine learning (ML) models, causing them to overlook rare, stealthy zero-day and infiltration attacks. This paper introduces a decentralized Cloud-Federated Intrusion Detection System that uses cooperative machine learning to train Deep Neural Networks (DNN) locally across distributed edge nodes. Our system operates on a Google Cloud Platform (GCP) coordinator layer and utilizes the Federated Averaging (FedAvg) algorithm to iteratively combine localized model weights, keeping raw network packets out of the cloud. To address severe class imbalance within edge nodes, we incorporate the Synthetic Minority Over-sampling Technique (SMOTE) locally before training. Rigorously tested against the CSE-CIC-IDS2018 benchmark dataset, the proposed architecture achieves a global accuracy of 86.78% and notable improvements in recall. It reaches a 100% detection rate for highly evasive WebAttacks and an 86% detection rate for stealthy Infiltration attacks.**

***Index Terms*—Intrusion Detection System, Federated Learning, Cooperative Machine Learning, SMOTE, Deep Neural Network, CSE-CIC-IDS2018.**

I. INTRODUCTION

The continuous evolution of cloud computing, multi-tenant digital infrastructures, and edge computing paradigms has completely transformed how modern enterprises process information. This architectural shift, however, has also drastically expanded the potential attack surface available to cyber adversaries. Modern organizations, ranging from critical healthcare facilities to multi-national banking systems, are forced to defend highly distributed networks against an array of sophisticated cyber threats. In this environment, Intrusion Detection Systems (IDS) serve as an indispensable line of automated, active defence by constantly parsing network metadata to isolate malicious activities.

Despite their vital importance, legacy machine learning-based IDS platforms suffer from structural design flaws that limit their effectiveness in modern networks. Conventional network anomaly detection relies on a centralized architectural paradigm [2], [6]. Under this setup, individual organizations must continuously mirror and transmit raw network packet streams across their administrative boundaries to a centralized cloud analytics engine for deep neural training or batch inference.

Beyond these architectural flaws, network security applications face a fundamental data engineering challenge: extreme class imbalance. Real-world network traffic repositories are notoriously asymmetrical, with standard baseline operations accounting for over 90% of the observations, while actual malicious exploits make up less than 10%. When exposed to this heavily skewed environment, traditional neural networks exhibit a phenomenon known as "lazy learning" [6]. Because they are optimized to maximize global accuracy scores, these models default their internal mathematical weight biases toward the majority class. Consequently, they achieve superficially high accuracy percentages while remaining completely blind to low-frequency, high-

impact anomalies such as stealthy multi-stage infiltrations and zero-day application exploits.

To solve both the architectural privacy bottleneck and the data imbalance challenge, this paper introduces a Cloud Intrusion Detection System using Cooperative Machine Learning. The proposed framework ensures complete data sovereignty by enforcing a strict data boundary: deep neural architectures are trained locally within each enterprise edge node, while an isolated Google Cloud Platform (GCP) instance aggregates only mathematical weight parameters using the Federated Averaging (FedAvg) algorithm. Concurrently, data imbalance is resolved at the source using localized Synthetic Minority Over-sampling Technique (SMOTE) configurations. This shifts the global model's optimization focus away from simple majority-class guessing and toward the precise identification of highly elusive network anomalies.

II. RELATED WORK

A review of the literature demonstrates the industry's ongoing transition away from simple, isolated cloud classifiers to highly intricate, distributed defense architectures.

Early cloud-based IDS models prioritized basic architectural evaluation. Ahmed [2] documented comparative analyses of classical supervised learning systems-such as Decision Trees, Support Vector Machines (SVM), and standard Neural Networks within cloud environments, illustrating that performance varies significantly depending on feature dimensionality and system dynamics. Concurrently, Manne [6] analyzed the integration of machine learning across commercial platforms, focusing on benchmark evaluation using legacy datasets like NSL-KDD and CICIDS2017 while emphasizing the persistent tension between system scalability and data privacy.

To bypass the requirement of relying on pristine, labeled datasets, unsupervised outlier detection paradigms became a major area of research. Kumar and Mathur [5] pioneered density-based unsupervised anomaly detection (DenOD) targeting cloud frameworks, highlighting that models can spot novel mutations without needing historical attack catalogs. Similarly, Casas et al. [7] constructed unsupervised network intrusion detection tools leveraging sub-space clustering and multiple evidence accumulation techniques to discover Distributed Denial of Service (DDoS) and scanning anomalies without relying on explicit training data. Pattanayak et al. [8] expanded on this by evaluating Generative Adversarial Networks (GANs) and Autoencoders, asserting that while deep unsupervised structures isolate general anomalies effectively, they often register higher false-alarm patterns due to their inability to distinguish benign variations from actual multi-stage malicious behaviour.

Rather than running deep single-instance topologies, alternative approaches explored ensemble and sequential setups. Gaikwad [4] implemented a Bagging ensemble approach utilizing reduced-error pruning trees (REPTree) to lower false-positive anomalies, showcasing the strength of bootstrap aggregation in reducing variance. Al-Ghuwairi et al. [1] framed intrusion monitoring uniquely as a time-series forecasting problem, utilizing Facebook Prophet combined with collaborative feature selection to isolate temporal dependencies and anomalies in cloud streams.

The closest evolutionary step toward our approach is documented by Olanrewaju-George and Pranggono [3] and Wang [9], who explored Federated Learning (FL) models for securing IoT and edge infrastructures. Their work demonstrates that decentralized weight training safely preserves node privacy. However, a major issue remains unaddressed across these decentralized models: when localized edge nodes encounter highly skewed internal datasets, the local gradients diverge wildly, which severely degrades the global aggregated model's accuracy and leads to high false negative rates for rare, critical attacks. Our research bridges this gap by embedding local SMOTE balancing pipelines natively inside an enterprise-grade Federated platform.

III. METHODOLOGY

1. Dataset

The CSE-CIC-IDS2018 dataset is a modern, authoritative cybersecurity benchmark created by the Communications Security Establishment (CSE) and

the Canadian Institute for Cybersecurity (CIC) [6]. Developed as a realistic alternative to outdated datasets like NSL-KDD, it captures sophisticated, multi-stage attacks within complex network topologies, reflecting contemporary enterprise and cloud traffic profiles.

The raw dataset contains millions of rows of network telemetry composed of 77 distinct features extracted from packet flow abstractions, including flow duration, forward/backward packet dimensions, inter-arrival times, and network flag configurations. While the original telemetry documents 15 granular sub-attack variations, training deep neural networks directly on heavily fractured labels can cause gradient fragmentation and degradation [2].

To optimize classification, the labels were consolidation mapped into 6 foundational Master Classes: Benign (normal operations), DoS/DDoS, Botnet, Infiltration (stealthy network penetration), Brute Force (FTP/SSH), and WebAttack (SQL injection and XSS).

Statistically, the dataset exhibits severe, naturally occurring class asymmetry, where baseline Benign traffic accounts for over 90% of total records, and stealth categories (such as WebAttacks) constitute less than 1%. This extreme class skew necessitates localized data rebalancing prior to cooperative machine learning deployment to prevent algorithmic blind spots [6].

2. Deep Neural Network (DNN) Architecture

To effectively ingest and process the massive, 3.7-million-row balanced feature matrix, we engineered a high-capacity sequential Deep Neural Network (DNN). While classical classifiers like Decision Trees and shallow Support Vector Machines are computationally constrained when scaled across modern multi-node cloud networks [2], a multi-layered feedforward neural topology excels at mapping highly non-linear relationships hidden across multi-vector flow logs.

The structural blueprint of our sequential deep learning architecture is organized as follows:

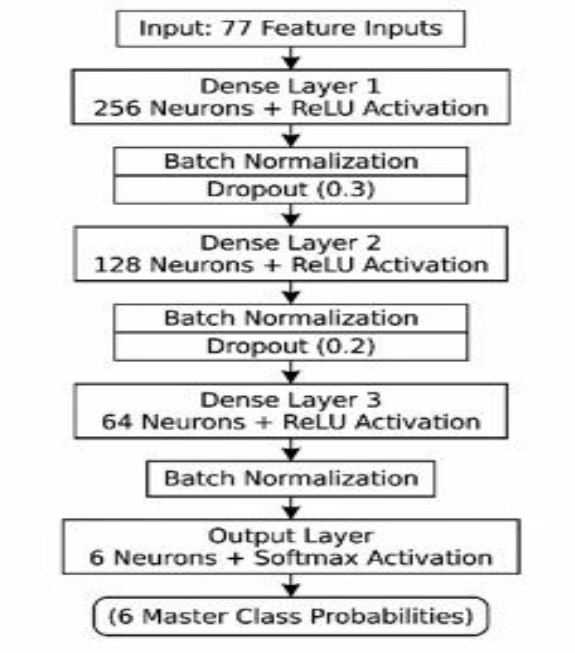

Fig 1. Deep Neural Network Architecture

The local sequential Deep Neural Network (DNN) processes 77 scaled feature inputs across a progressively condensed network layout designed to map complex, non-linear threat vectors [2].

- Hidden Layer 1 (Feature Extraction): Contains 256 dense units utilizing the Rectified Linear Unit (ReLU) activation function, f(z)=max(0, z). It is integrated with Batch Normalization to prevent internal covariate shift and regulated by a 0.3 Dropout rate to eliminate over-specialization on synthetic patterns.
- Hidden Layer 2 (Abstract Mapping): Comprises 128 dense units (ReLU) paired with Batch Normalization and a 0.2 Dropout rate to safeguard generalization boundaries across distributed nodes.
- Hidden Layer 3 (Refinement Layer): Features 64 dense units (ReLU) and a final Batch Normalization step to refine extracted features into distinct threat signatures.
- Output Layer (Classification): Consists of 6 dense units driven by a Softmax function, converting raw logit arrays into an explicit probability distribution:

$$P(y = c|x) = \frac{e^{z_c}}{\sum_{j=1}^{6} e^{z_j}}$$

The framework uses the Adam Optimizer to dynamically compute adaptive learning rates by tracking gradient moments, preventing gradient stalling during mixed attack spikes [6]. Training error is minimized using a Sparse Categorical Crossentropy loss objective:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N} \log P\,(y_i|x_i)$$

This mathematical structure guarantees that edge-trained weights highly preserve minority attack signatures before uploading parameters to the global GCP federated coordinator.

3. Federated Learning System Architecture and Coordination Loop

To enforce strict data privacy across participating enterprise institutions, the traditional centralized data pooling pipeline is replaced with a decentralized, cooperative learning topology. Rather than continuously streaming raw network packet data over public networks to a single server-which exposes organizations to compliance risks and single-point-of-failure vulnerabilities [2], [6] - the network architecture isolates the underlying training pools within local enterprise boundaries.

The system relies on a decentralized topology composed of two main architectural layers:

1. The Edge Layer: Distributed nodes configured natively inside separate enterprise infrastructures. These nodes manage their own data pipelines, scale their features using StandardScaler, and balance their internal traffic distributions using localized SMOTE before initiating deep backpropagation cycles.
2. The Cloud Coordination Layer: A centralized Google Cloud Platform (GCP) instance. This instance has no attached storage mounts for network traffic logs and no direct access to individual packet flows [3].

The cooperative training mechanism runs iteratively over a series of sequential global communication rounds, executing a privacy-preserving loop:

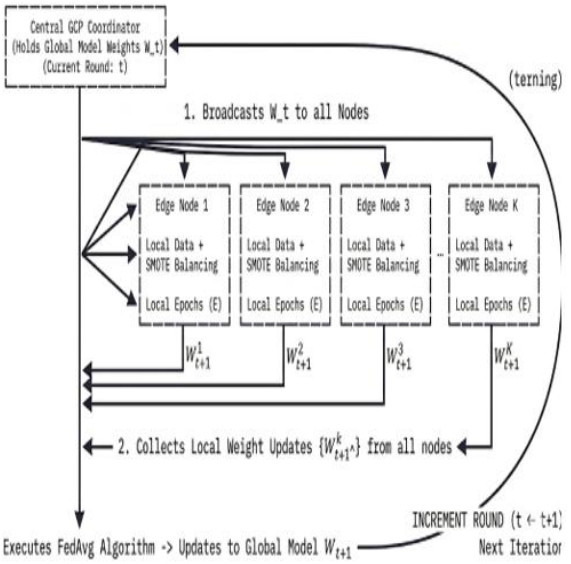

Fig 2. Iterative Federated Learning with SMOTE – Balanced Edges Nodes

1. Global Weight Distribution: The GCP coordinator distributes the global model parameters to all edge nodes at the start of each communication round.
2. Localized Parallel Training: Each node trains the received model locally using its balanced dataset with Adam optimizer and Sparse Categorical Crossentropy loss.
3. Parameter Upload: Updated weights and bias tensors are extracted and securely uploaded to the cloud coordinator.
4. Cloud Aggregation: The server combines all uploaded parameters using the Federated Averaging (FedAvg) algorithm.

4. The Federated Averaging (FedAvg) Mathematical Framework

The GCP server performs centralized mathematical aggregation by computing a normalized, sample-weighted average of neural network parameters received from all distributed edge nodes. Each node contributes proportionally based on the size of its locally trained and SMOTE-balanced dataset, ensuring fair participation without centralizing raw network traffic. After local training, updated weights and bias tensors are uploaded to the cloud and combined using the Federated Averaging (FedAvg) algorithm to generate a unified global model. This collaborative aggregation improves the detection of rare cyberattacks such as Infiltration and WebAttacks while preserving data privacy. The updated global

model is redistributed for the next communication round.

IV. CIDS WORKFLOW

The proposed Cloud Intrusion Detection System (IDS) operates using a distributed Federated Learning architecture where multiple edge nodes collaboratively train a global Deep Neural Network (DNN) model without sharing private network data.

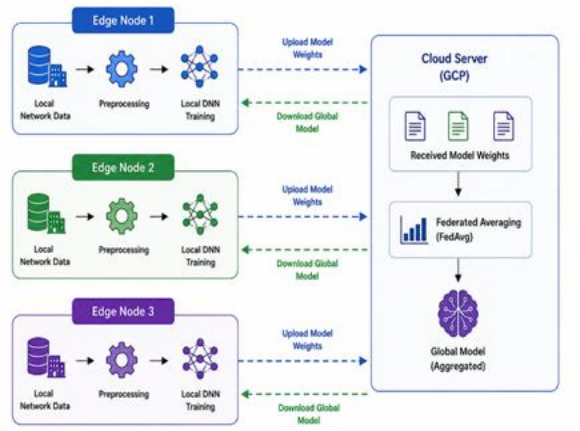

Fig 3. Proposed Workflow of CID System

The workflow shown in the architecture diagram is explained below.

The proposed cloud intrusion detection system consists of multiple distributed edge nodes, where each node represents an independent organization or local network environment. Every edge node collects and stores its own private network traffic data, including both normal and malicious traffic. Data preprocessing and feature preparation are performed locally to ensure that sensitive information never leaves the organization. After preprocessing, each node independently trains a local Deep Neural Network (DNN) model using its private dataset for several local epochs.

Instead of sharing raw datasets with the cloud, each edge node uploads only the trained model weights and bias parameters to the centralized cloud server hosted on Google Cloud Platform. The cloud server acts as the coordination layer of the federated system. It receives model parameters from all participating nodes and applies the Federated Averaging (FedAvg) algorithm to combine the learned knowledge into a unified global model. This aggregation process preserves data privacy while improving attack detection capability.

The updated global DNN model is then redistributed back to all edge nodes. Each node replaces its previous local model with the new global model, and the federated learning cycle continues for multiple communication rounds until convergence is achieved.

V. EXPERIMENTAL RESULT

1. Training Performance

The proposed Cloud Intrusion Detection System using Co-Operative Machine Learning Technique successfully trained a DNN model across three distributed edge nodes using Federated Learning with a centralized Google Cloud Platform server. SMOTE balancing significantly improved minority attack detection, enabling stable model convergence and enhanced classification accuracy for rare attacks like Infiltration and WebAttack across all six classes.

2. Global Model Accuracy

The final aggregated global model achieved an overall classification accuracy of: Accuracy = 86.78%

Although the accuracy was moderate, the model demonstrated excellent minority-class detection capability, which is more important in cybersecurity environments.

3. Recall Performance for Minority Attacks

The major achievement of the proposed framework was the significant improvement in Recall values for rare cyberattacks.

A. WebAttack Detection: The model successfully detected all WebAttack samples in the testing dataset.

Table II WebAttack Detection Performance

Metric	Value
Total WebAttack Samples	167
Correctly Detected	167
Recall	100%

This result proves that the proposed federated framework effectively learned stealthy web-based attack patterns.

B. Infiltration Detection: The model also demonstrated strong performance for infiltration attacks, which are

generally difficult to detect due to their stealthy behaviour.

Table III Infiltration Detection Performance:

Metric	Value
Total Infiltration Samples	23,519
Correctly Detected	20,202
Recall	86%

The high recall value indicates that the IDS became highly sensitive to sophisticated intrusion attempts.

4. Result Of Classification Report and Confusion Matrix

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============================================================
📊 DETAILED CLASSIFICATION REPORT
============================================================
              precision    recall  f1-score   support

      Benign       0.96      0.62      0.76    106561
      Botnet       0.99      0.99      0.99     29068
  BruteForce       1.00      1.00      1.00     18923
    DoS_DDoS       1.00      1.00      1.00    154675
Infiltration       0.34      0.86      0.49     23519
   WebAttack       0.07      1.00      0.14       167

    accuracy                           0.87    332913
   macro avg       0.73      0.91      0.73    332913
weighted avg       0.94      0.87      0.88    332913
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Fig 3. Classification Report

The classification report shows strong detection performance for Botnet, BruteForce, and DoS-DDoS attacks with near-perfect precision and recall However Benign traffic has moderate recall while Infiltration and WebAttack classes suffer from low precision indicating false positives Overall model accuracy reaches 87% with performance.

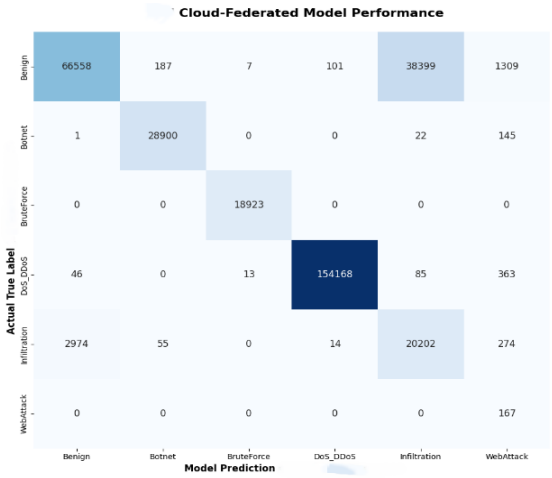

Fig 5. Confusion matrix

The confusion matrix demonstrates excellent classification for Botnet, BruteForce, DoS_DDoS, and WebAttack classes, with most predictions correctly identified along the diagonal Benign and Infiltration classes show noticeable misclassifications, especially between each other, indicating overlapping traffic patterns Overall, the federated model achieves detection performance

VI. CONLUSION

This research proposed a Cloud Intrusion Detection System (IDS) using Co-Operative Machine Learning Technique, Deep Neural Networks (DNN), and SMOTE to improve cybersecurity threat detection while preserving data privacy. Unlike traditional centralized IDS systems, the proposed framework allows multiple edge nodes to train locally on private network traffic without sharing raw data. Only model weights are exchanged with the cloud server, where the Federated Averaging (FedAvg) algorithm generates a global model.

The CSE-CIC-IDS2018 dataset was used along with preprocessing techniques such as feature scaling and class mapping. SMOTE successfully balanced minority attack classes, significantly improving the detection of rare attacks. Experimental results achieved approximately 86.78% global accuracy, 100% WebAttack detection recall, and 86% Infiltration recall. The final deployed model demonstrated real-time intrusion detection capability, proving the effectiveness, scalability, and privacy-preserving nature of the proposed federated cybersecurity framework.

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