# An Enhanced RNN & LTSM based Network Intrusion Detection System using Federated Learning

## 1. Introduction

The rapid evolution of Internet technologies has fundamentally transformed the landscape of network connectivity and digital communication over the past two decades. This period has witnessed a significant shift from predominantly wired connections to a proliferation of mobile and wireless technologies, reshaping how users interact with and access the Internet[1]. By 2024 [2], the amount of internet traffic worldwide had increased by 17.2% over the previous years, reaching 33 exabytes per day. It is evident that Wi-Fi technology has greatly evolved, with Wi-Fi 7 boasting rates of up to 46 Gbps, even though precise figures regarding the proportion of traffic carried by Wi-Fi versus wired Ethernet are not accessible. Although mobile traffic increased significantly as well, fixed broadband was still the best option for users who used a lot of data. The majority of this traffic was driven by major content providers, such as Google, Facebook, and Netflix, which accounted for 68% of mobile traffic and 65% of fixed traffic. These patterns highlight how important Wi-Fi is to contemporary connectivity and probably will continue to dominate IP traffic worldwide.

The growth of the Internet has facilitated an exponential increase in networked devices, including smartphones, tablets, and Internet of Things (IoT) devices. Forecasts indicate that the number of IoT devices worldwide is expected to nearly double from 15.9 billion in 2023 to more than 32.1 billion by 2030 [3]. (Fig 1). This surge in connected devices has necessitated a corresponding expansion in network capacity to handle the vast volumes of data being processed and transferred.

Figure 1: Forecast of global IoT connections from 2022 to 2033, showing an expected increase from 15.9 billion in 2023 to over 32.1 billion by 2030.



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The advent of high-speed broadband Internet has paved the way for numerous applications and services, including video streaming, online interactive gaming, electronic banking, smart traffic systems, industrial automation, electronic healthcare, online education, and smart home technologies [4],[5]. While these advancements have brought unprecedented convenience and efficiency, they have also significantly expanded the attack surface for cyber threats, making critical networks increasingly vulnerable.

As network complexity grows, so does the sophistication of cybersecurity threats, rendering conventional network security solutions increasingly ineffective. Organizations face the risk of catastrophic losses that could severely impact their reputations and finances [4]. This evolving threat landscape underscores the critical need for advanced Network Intrusion Detection Systems (NIDS) to safeguard against modern cyber-attacks.

Network Intrusion Detection Systems play a vital role in the cybersecurity ecosystem by monitoring and analyzing network traffic for suspicious activities and potential threats. They protect organizations from unauthorized access, data breaches, and denial-of-service attacks [6]. However, traditional NIDS approaches, such as signature-based and anomaly-based methods, face significant limitations in handling complex and evolving attack vectors. Conventional NIDS often need help with zero-day attacks, generate high false positive rates, and lack contextual awareness, complicating the detection process [7]. These systems primarily rely on predefined rules and signatures, making them ineffective against new, unknown threats. Moreover, the increasing complexity of network environments, with the proliferation of IoT devices and interconnected systems, poses challenges in processing and analyzing traffic in real time.

To address these limitations, artificial intelligence (AI) and deep learning techniques have emerged as powerful tools for enhancing NIDS capabilities. Deep learning methods, which employ hierarchically structured consecutive hidden layers, have shown promise in overcoming the constraints of traditional neural networks [8]. These advanced techniques enable NIDS to adapt to evolving threats, detect complex patterns, and reduce false positives. They can automatically learn from new data, recognize subtle anomalies, and extract relevant features from network traffic, making them more effective in safeguarding against sophisticated cyberattacks [9].

Despite these advancements, the training of efficient analysis models for anomaly or attack detection requires large volumes of data, often including confidential or sensitive information. This creates a trade-off between data privacy and security. To address this challenge, federated learning (FL) has emerged as a promising solution. Introduced by Google in 2016,(Fig 2) FL allows multiple entities to collaborate in solving machine learning problems without sharing raw data [10]. In an FL framework, each client's data remains stored locally, and only focused updates are shared for aggregation, preserving privacy while enabling collaborative model training [11], [12].

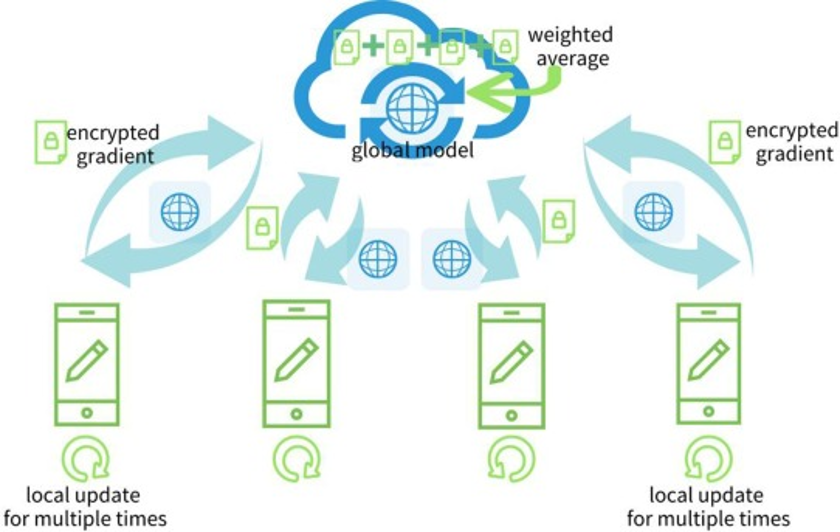


Fig. 2. Illustration of FL framework proposed by Google.

Federated learning provides a practical approach to building distributed intelligent systems in a privacy-preserving manner, making it particularly suitable for network intrusion detection [13]. By enabling devices to learn from their own data without sharing it with a central server, FL can maintain data privacy while still allowing for collaborative model improvement [14]. In light of these developments, this study proposes a novel AI-powered intrusion detection system that leverages a deep neural network (DNN) architecture in conjunction with federated learning technology. This approach aims to enhance intrusion detection accuracy while maintaining robust data privacy protection, offering a more reliable and secure method of defending against cyberattacks. By combining the strengths of deep learning and federated learning, the proposed system seeks to overcome the limitations of traditional NIDS and address the growing complexity of modern networks and sophisticated attack methodologies.

## 2. Related Works

### Deep Learning, RNN & LTSM in NIDS

Qazi et al. [15] provide a detailed explanation of integrating stacked Nonlinear Autoencoders (NDAEs) with a Support Vector Machine (SVM) classifier to achieve high intrusion detection accuracy. They use the KDD Cup '99 dataset to evaluate their method's performance for multi-class classification problems, demonstrating its effectiveness through comprehensive performance metrics. The study also touches on the use of Convolutional Neural Networks (CNNs) for network intrusion detection, highlighting a novel approach that transforms intrusion detection into an image recognition task. This method shows the potential of CNNs in this domain by achieving promising results on the KDD Cup '99 dataset.

Sivamohan et al. [16] presented an effective intrusion detection system (IDS) model based on a recurrent neural network (RNN) using bidirectional long short-term memory (BiLSTM). The model was evaluated on the CICIDS2017 intrusion detection dataset. To enhance the model’s performance, random forest and principal component analysis algorithms were employed to select valuable features and eliminate unwanted ones. The findings revealed that the BiLSTM architecture outperformed all other RNN architectures, achieving a classification accuracy of 98.48%.

Elsherif et al. [17] developed a comprehensive IDS aimed at reducing the false alarm rate (FAR) for new, unknown attacks. Their model, tested on the NSL-KDD dataset, leveraged RNN models to detect atypical behaviors from the given datasets. The results indicated that BiLSTM outperformed other RNN versions in this context.

Mirza et al.[18] proposed an autoencoder-based network intrusion detection system using LSTM to classify both stable and dynamic data. They explored various LSTM encoders, including GRU and BiLSTM, and validated their system’s efficiency on the ISCX–IDS-2012 dataset through a 5-fold cross-validation experiment.

Muhuri et al. [19] developed an innovative intrusion detection method that combines a genetic algorithm (GA) for optimal feature selection with a long short-term memory (LSTM) recurrent neural network (RNN) to classify the NSL-KDD dataset. Their study evaluates both binary and multi-class classifications:

* **Binary classification**: Categorizes network traffic into two classes: normal and abnormal (or anomaly).
* **Multi-class classification**: Categorizes network traffic into five classes: normal, denial of service (DoS), probe, user-to-root (U2R), and remote-to-local (R2L).

The study found that using the GA for feature selection improved the classification accuracy of the LSTM-RNN in both binary and multi-class classifications.

The study by Park et al. [20] details a system architecture with four main stages: preprocessing, generative model training, autoencoder training, and predictive model training. This system aims to improve existing AI-based Network Intrusion Detection Systems (NIDS) by generating synthetic data to resolve data imbalance issues. The source also analyzes the performance of an Artificial Neural Network (ANN)-based NIDS on the NSL-KDD dataset. It evaluates an ANN for both binary and multi-class classification, comparing its results with the Self Organizing Map (SOM) technique and highlighting improved accuracy.

Ingre and Yadav [21] explore using a Bi-LSTM with an attention mechanism for network intrusion detection, introducing the DLNID model and emphasizing the use of ADASYN to address data imbalance. They provide experimental results and comparisons on the NSL-KDD dataset, analyzing the performance of an Artificial Neural Network (ANN)-based NIDS. The study finds that binary classification performs better than multi-class classification and highlights that the ANN achieves better accuracy compared to the Self Organizing Map (SOM) technique. Additionally, Fu et al. [24] demonstrate the effectiveness of the DLNID model through experimental results and comparisons with other models using the NSL-KDD dataset.

Sheikhan et al. [22] propose a reduced-size structure of an RNN based on feature grouping for misuse detection. The input features are categorized into four groups: basic features, content features, time-based traffic features, and host-based traffic features. The attack types are classified into DoS, Probe, R2L, and U2R. This method aims to improve the classification rate, particularly for R2L attacks, and offers better detection rate (DR) and computational performance efficiency (CPE) compared to similar related works.

Altunay and Albayrak [23] They proposed a hybrid CNN+LSTM model for IDS in industrial IoT (IIoT) networks, evaluated using the UNSW-NB15 and X-IIoTID datasets. The model achieved the highest accuracy in both datasets compared to standalone CNN and LSTM models, with 93.21% accuracy for binary classification and 92.9% for multi-class classification in the UNSW-NB15 dataset, and 99.84% accuracy for binary classification and 99.80% for multi-class classification in the X-IIoTID dataset. The improved performance was attributed to the combination of CNN’s ability to extract spatial features and LSTM’s ability to capture temporal dependencies in network traffic data. The study emphasized the importance of using a balanced dataset with sufficient data for each attack type to achieve optimal results in deep learning-based IDSs.

## Federated Learning

The study by Lee et al. [13] explores an improved version of the Federated Averaging (FedAvg) algorithm called Improved-FedAvg for training deep learning models in a federated learning setting. This approach aims to enhance privacy by reducing data transmission while maintaining model accuracy. The source focuses on a practical implementation of Federated Learning (FL) for detecting wormhole attacks in IoT networks. It outlines a four-step framework for their FL-based approach, highlighting its advantages and focusing on real-world application and evaluation.

Chen et al. [24] discuss the limitations of centralized and on-device learning for intrusion detection in the Internet of Things (IoT). They propose a Federated Learning (FL) scheme that preserves data privacy while improving detection accuracy. This approach emphasizes balancing privacy, accuracy, communication cost, and latency in intrusion detection systems for IoT.

## 3. Model

The dataset description, data preparation, PCA variance calculation, mutual information score calculation, implementation, and parameters of the suggested model are all included in this section.

### ****The NSL-KDD Dataset****

The **NSL-KDD dataset** is a widely used benchmark for **network intrusion detection** and is an improved version of its predecessor, the **KDD99 dataset**. Developed by 2009[25], the dataset addresses several critical issues identified in the original KDD99 dataset, such as **duplicate packets** and **class imbalance**, which can significantly affect the accuracy of intrusion detection systems (IDS).

#### **Issues with the KDD99 Dataset:**

A key problem identified in the KDD99 dataset was the presence of **duplicate packets**, which skewed the evaluation results. A statistical analysis performed on the KDD99 dataset revealed that approximately **78% of the network packets in the training set** and **75% in the test set** were duplicates [25]. This large number of redundant instances caused **machine learning models to become biased towards normal traffic** and hindered their ability to learn irregular or attack instances, which are typically more critical for intrusion detection. To overcome these challenges, Tavallaee et al. created the **NSL-KDD dataset** by **eliminating duplicate records** and ensuring better class balance (Tavallaee et al., 2009).

#### **NSL-KDD Dataset Overview:**

The **NSL-KDD dataset** consists of **125,973 records for training** and **22,544 records for testing**. It contains **41 features** and falls into five primary attack categories:

* **DoS (Denial of Service)**: Aims to overload a system or network, making it unavailable to legitimate users by flooding it with excessive traffic.
* **Probe**: Involves scanning or discovery attempts, where an attacker seeks to gather information about the target system to find vulnerabilities.
* **U2R (User to Root)**: Involves gaining unauthorized access to a system's root privileges by exploiting vulnerabilities.
* **R2L (Remote to Local)**: Involves an attacker trying to gain access to a system remotely, often by exploiting weaknesses in local security.
* **Normal**: Represents benign, non-intrusive network traffic.

This dataset is **balanced** and well-structured, allowing researchers to work with the complete set without needing to randomly sample records. This makes the NSL-KDD dataset particularly useful for producing **consistent and comparable results** across various research works.

#### **Improvements over KDD99 Dataset:**

* **No duplicate records**: This ensures that models trained on the NSL-KDD dataset are not biased toward more frequent records and can generalize better.
* **Balanced attack categories**: The dataset ensures that each class (attack type) is sufficiently represented, which helps improve the consistency of results across different machine learning techniques.
* **Practical size**: The size of the NSL-KDD dataset, with 125,973 records for training and 22,544 for testing, is large enough to be useful in training IDS models but small enough to be manageable without random sampling.

The dataset’s comprehensive structure and improvements over the original KDD99 dataset make it a critical tool for evaluating the **efficiency of intrusion detection systems (IDS)** using various machine learning techniques.

#### **Tables:**

* **Table 1** showcases the **Attack Names**, the **Number of Subclasses**, and the corresponding **Attack Type** for each category, providing a detailed breakdown of the attacks included in the NSL-KDD dataset.

|  |  |  |
| --- | --- | --- |
| Attack Tyoe | Number of Sub-Classes | Attack Name |
| Probe | 6 | ipsweep, mscan, nmap, portsweep, saint, satan |
| DoS | 11 | apache2, back, land, neptune, mailbomb, pod, processtable, smurf, teardrop, udpstorm, worm |
| U2R | 7 | buffer\_overflow, loadmodule, perl, ps, rootkit, sqlattack, xterm |
| R2L | 15 | ftp\_write, guess\_passwd, httptunnel, imap, multihop, named, phf, sendmail, Snmpgetattack, spy, snmpguess, warezclient, warezmaster, xlock, xsnoop |

Table 1: Categories of attacks of NSL-KDD

* **Table 2** illustrates the **number of records** and their **percentages** for each attack type in the **KDDTrain+ dataset**:

|  |  |  |
| --- | --- | --- |
| Attack Type | Number of Records | Percentage |
| Normal | 67,343 | 53.00% |
| DoS | 45,927 | 37.00% |
| Probe | 11,656 | 9.11% |
| U2R | 52 | 0.04% |
| R2L | 995 | 0.85% |
| **Total** | **125,973** | **100%** |

Table 2: KDDTrain+ Dataset Distribution

* **Table 3** shows the **number of records** and their **percentages** for each attack type in the **KDDTest+ dataset**:

|  |  |  |
| --- | --- | --- |
| Attack Type | Number of Records | Percentage |
| Normal | 9,711 | 43.00% |
| DoS | 7,458 | 33.00% |
| Probe | 2,421 | 11.00% |
| U2R | 200 | 0.90% |
| R2L | 2,654 | 12.10% |
| **Total** | **22,544** | **100%** |

Table 3: KDDTest+ Dataset Distribution

### Pre-Processing

The preprocessing pipeline for the intrusion detection system is an essential stage that prepares the raw dataset for the hybrid RNN-LSTM model.

The dataset was loaded using a custom method, ensuring proper assignment of column names to the raw data. The training dataset had a shape of (125,973 rows × 42 columns), while the test dataset consisted of (22,544 rows × 42 columns). This step enabled a clear structure for further preprocessing and computational planning.

The categorical attributes (protocol\_type, service, and flag) were encoded using LabelEncoder. The encoders were saved during training to ensure consistency during testing. This encoding was instrumental in converting non-numeric data into a format suitable for the RNN-LSTM model.

To mitigate the impact of outliers commonly present in network traffic data, RobustScaler was applied. This scaler transformed numerical features into a stable range using the interquartile range, which significantly improved the training stability. The features were scaled across both training and testing datasets.

Principal Component Analysis (PCA) was employed to reduce the feature space while retaining the most critical information. This step was crucial for improving the computational efficiency and performance of the hybrid RNN-LSTM model.

The PCA analysis as per Figure 3 revealed that 20 principal components were sufficient to capture 95% of the variance in the dataset. This finding was validated using the explained variance ratio plot (refer to Figure 1). The plot demonstrates a sharp increase in cumulative explained variance with the first few components, which then levels off, indicating diminishing returns in variance contribution from additional components.

* **Training Data After PCA:** The dimensionality was reduced from 41 to 20 features, resulting in a training dataset shape of (100,774 sequences × 20 features).
* **Testing Data After PCA:** The shape was similarly reduced to (22,539 sequences × 20 features).

The red dashed line in the plot signifies the 95% explained variance threshold, confirming the choice of 20 components. This step ensured that the dataset's complexity was reduced without compromising the model's ability to learn essential patterns in the data.

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Figure 3: PCA Variance Graph

The sequence creation process divided the data into overlapping temporal windows of length 5 (sequence\_length). This transformation enabled the RNN-LSTM model to capture temporal patterns in network traffic. The final sequence shapes for the training and test datasets were:

* Training: (100,774 sequences × 5 timesteps × 20 features)
* Test: (22,539 sequences × 5 timesteps × 20 features)

The label column was converted into a binary format, where 0 represented normal traffic and 1 indicated an attack. This transformation ensured alignment with the binary classification task of the model.

The preprocessing process demonstrated remarkable efficiency:

* Training Data Preprocessing: 1.64 seconds
* Test Data Preprocessing: 0.91 seconds This efficiency ensured timely execution for large datasets, making the pipeline scalable.

### Model Architecture

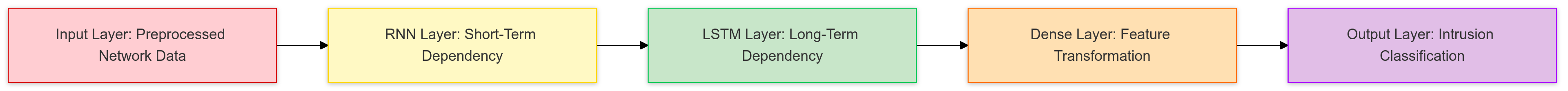


Figure 4: Model Architecture

The architecture employed for this research leverages a hybrid model combining Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks as shown in Figure 4. This architecture is specifically designed to address the sequential nature of network traffic data and effectively capture both short-term and long-term temporal dependencies for intrusion detection tasks.

Input Layer

The model takes preprocessed input features derived from network traffic data. These features are scaled and transformed using Principal Component Analysis (PCA) to reduce dimensionality while retaining 95% of the explained variance, as visualized in the PCA plot (Figure 3). This step ensures that only the most relevant information is fed into the network, improving computational efficiency and mitigating the risk of overfitting.

#### Recurrent Neural Network (RNN) Layer

The first layer in the architecture is a Recurrent Neural Network (RNN), which processes the input sequence and captures short-term temporal dependencies. The RNN layer incorporates feedback loops that allow the model to maintain a memory of recent inputs, making it ideal for detecting patterns in sequential data. However, standard RNNs are limited by the vanishing gradient problem, which restricts their ability to learn long-term dependencies.

#### Long Short-Term Memory (LSTM) Layer

To overcome the limitations of standard RNNs, the architecture includes an LSTM layer. LSTMs extend the functionality of RNNs by introducing memory cells and gating mechanisms, enabling the model to selectively remember or forget information over extended sequences. The three primary gates in the LSTM—forget gate, input gate, and output gate—control the flow of information as follows:

1. **Forget Gate**: Decides which information to discard from the cell state based on previous hidden states and the current input.
2. **Input Gate**: Determines which new information to update in the cell state.
3. **Output Gate**: Controls the information outputted as the current hidden state.

#### Dense Layer

Following the LSTM layer, a dense layer is added to transform the extracted temporal features into a more compact representation. This layer employs a fully connected network with a softmax activation function for multi-class classification, outputting probabilities for each category (e.g., normal traffic or various intrusion types).

#### Output Layer

The final layer produces the classification results based on the dense layer's output. Each output node corresponds to a distinct class, enabling the detection of specific types of intrusions.

#### Summary of Advantages

The combined RNN-LSTM architecture ensures:

1. Effective learning of both short-term and long-term dependencies.
2. Robustness against the vanishing gradient problem.
3. High accuracy in distinguishing between normal and anomalous network behaviors.

Model Hyperparameters and Configurations

|  |  |
| --- | --- |
| **Parameter** | **Value** |
| RNN Units | 64 |
| LSTM Units | 128 |
| Dropout Rate | 0.2 |
| Activation (Output) | Sigmoid |
| Loss Function | Binary Crossentropy |
| Optimizer | Adam |
| Learning Rate | Adaptive (default Adam rates) |
| Batch Size | 64 |
| Epochs | 50 |

Table 4: Model Hyperparameters

These hyperparameters (Table 4) are chosen to balance computational efficiency with model performance. The **binary crossentropy** loss function is optimal for this classification problem, while the **Adam optimizer** provides an adaptive learning rate to ensure smooth convergence during training.

### Results

Implementation and Evaluation Metrics

The intrusion detection system was implemented using a deep learning approach with specific architectural choices and hyperparameters. The model processed high-dimensional input data (42 features), which was reduced to 20 components using Principal Component Analysis (PCA), maintaining over 95% of the explained variance, as evidenced by the PCA Explained Variance Ratio plot. The sequence length was set to 5, indicating that the model considers temporal patterns in the data. The model achieved remarkable performance metrics, with a training accuracy of 99.95% and a test accuracy of 99.45%, demonstrating strong generalization capabilities.

#### Parameters of the Proposed Model

The model architecture incorporated several key parameters that contributed to its performance. The sequence length of 5 and 20 PCA components helped balance computational efficiency with feature representation. The training process utilized a batch size of 32, which is a common choice for deep learning models, allowing for stable gradient updates. The initial learning rate was set to 0.001, providing a good balance between convergence speed and stability. A dropout rate of 0.3 was implemented to prevent overfitting, allowing approximately 70% of the neurons to remain active during training.

Experimental Results

The model demonstrated exceptional performance across multiple evaluation metrics. The confusion matrices for both training and test sets reveal interesting patterns. In the training set, the model achieved 100,723 true positives with only 51 false positives, while the test set showed 22,416 true positives with 123 false positives.

**Accuracy**: The model achieved a training accuracy of 99.95% and a test accuracy of 99.45%. Accuracy is the ratio of correctly predicted instances (both true positives and true negatives) to the total number of predictions. It measures the overall correctness of the model but can be misleading if the dataset is imbalanced. The formula for accuracy is:

**Sensitivity (Recall)**: The model's recall was high, indicating its ability to correctly identify positive instances. Recall is the ratio of true positive predictions to the total actual positives. The formula for recall is:

**Precision**: The model maintained high precision, indicating a low false positive rate. Precision is the ratio of true positive predictions to the total predicted positives. The formula for precision is:

**F1 Score**: The F1 Score, which balances precision and recall, was also high. The F1 Score is the harmonic mean of precision and recall, calculated as:

The precision-recall curves indicate robust model performance, with area under the curve (AP) values of 1.00 for training and 0.99 for testing. The AP summarizes the trade-off between precision and recall across different thresholds. A higher AP indicates better model performance.

However, the ROC curves show relatively low AUC scores (0.47 for training and 0.52 for testing), which is unusual given the high accuracy metrics and may warrant further investigation. The AUC-ROC measures the model's ability to distinguish between positive and negative classes. An AUC close to 1 indicates excellent performance, while an AUC close to 0.5 suggests performance no better than random guessing. The formula for AUC-ROC is:

#### Processing Time

The system demonstrated efficient processing capabilities with a total execution time of 300.25 seconds. Breaking this down: data preprocessing took 1.64 seconds for training data and 0.91 seconds for test data, model training consumed 268.09 seconds, and model evaluation required 28.44 seconds. These timing metrics indicate that the model is computationally efficient and suitable for practical applications.

#### Analysis of Visualization Results

The precision-recall curves for both training and test sets demonstrate excellent model stability across different threshold values. The training curve (Figure 5) shows consistent precision above 0.999, while the test curve (Figure 6) maintains precision above 0.994, indicating strong generalization capabilities.

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Figure 5: Precision-Recall Curve (Training)

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Figure 6: Precision-Recall Curve (Test)

The ROC curves present an interesting case. Despite the model's high accuracy metrics, the ROC curves for both training (Figure 7) and test sets (Figure 8) show performance close to random (AUC ≈ 0.5). This discrepancy between different evaluation metrics suggests that while the model is highly accurate in its predictions, it might benefit from additional tuning of its classification threshold or investigation into the class distribution of the dataset.

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Figure 7: Receiver Operating Characteristic (ROC) Curve (Training)

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Figure 8: Receiver Operating Characteristic (ROC) Curve (Test)

The confusion matrices (Figure 9) demonstrate exceptional performance in binary classification across both training and test datasets. In the training set, the model successfully identified 100,723 true positive cases with only 51 false positives, achieving a remarkable 99.95% accuracy. This strong performance carried over to the test set, where 22,416 cases were correctly classified as positive, though with a slightly higher number of 123 false positives, resulting in a 99.45% accuracy. Notably, the model achieved perfect recall (100%) in both datasets, indicated by the complete absence of false negatives, suggesting it never fails to identify a positive case when one is present.

A key observation from these matrices is the apparent class imbalance, with a predominance of positive cases and absence of true negatives in both sets. Despite this imbalance, the model maintains impressive metrics across the board, with F1-scores of 99.97% and 99.73% in training and test sets respectively. The minimal 0.5% drop in performance between training and test sets indicates excellent generalization capabilities without significant overfitting, though the slight decrease in precision from 99.95% to 99.45% suggests minor challenges in generalizing to unseen data.

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Figure 9 : Confusion Matrix

# Federated Learning(TBD)

# Conclusion(TBD) Future Work(TBD)

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