

# SPLIT LEARNING-BASED SECURE TRAFFIC CLASSIFICATION FOR PRIVACY-SENSITIVE NETWORKS

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**Abstract** - The rapid growth of networked systems and encrypted communications has made network traffic classification a critical component of modern cybersecurity. However, traditional traffic classification techniques, particularly centralized machine learning and Deep Packet Inspection (DPI), pose significant privacy risks due to their reliance on direct access to sensitive network data. Although federated learning offers partial privacy preservation, it remains vulnerable to information leakage through shared gradients. To address these challenges, this paper proposes a split learning-based secure traffic classification framework designed for privacy-sensitive network environments. In the proposed approach, a deep neural network is partitioned between client devices and a central server, enabling collaborative model training without sharing raw network traffic data. Clients process local data through initial layers and transmit only intermediate activations to the server, which completes classification and returns gradients for model updates. The framework is evaluated using benchmark datasets, including CICIDS2017 and UNSW-NB15, with performance measured through accuracy, precision, recall, and F1-score. Experimental results demonstrate that the proposed model achieves high classification accuracy while significantly enhancing data privacy compared to centralized and traditional machine learning approaches. The findings highlight that split learning provides an effective balance between privacy preservation and model performance, making it a promising solution for secure traffic analysis in modern distributed network environments.

**Key Words:** Split Learning, Traffic Classification, Privacy-Preserving Machine Learning, Network Security, Deep Learning, Intrusion Detection, Distributed Learning.

## 1. INTRODUCTION

The rapid evolution of digital communication technologies has transformed modern network infrastructures, leading to unprecedented growth in data generation and transmission. With the proliferation of cloud computing, Internet of Things (IoT), and real-time applications, networks have become highly dynamic and complex. This growth has significantly increased the demand for intelligent traffic monitoring and classification systems to ensure network security and performance. However, the integration of machine learning techniques into traffic analysis has introduced new

challenges related to data privacy and security. Traditional approaches often rely on centralized data collection, which exposes sensitive information and creates vulnerabilities in privacy-sensitive environments. Therefore, developing secure and privacy-preserving traffic classification mechanisms has become a critical research priority in modern cybersecurity systems (Cisco, 2023; Nguyen and Armitage, 2008).

## 1.1 Background

### 1.1.1 Growth of Network Traffic and IoT Ecosystems

The expansion of IoT devices and digital services has led to exponential growth in global network traffic. Modern networks support a wide range of applications, including smart healthcare, industrial automation, and cloud-based services, all of which continuously generate large volumes of data. This rapid increase in traffic complexity necessitates advanced analytical techniques to monitor and manage network behavior effectively. Traditional rule-based systems are no longer sufficient to handle such scale and diversity, leading to the adoption of machine learning and deep learning methods for traffic analysis (Aceto, Ciunzo and Montieri, 2019).

### 1.1.2 Importance of Traffic Classification in Cybersecurity

Traffic classification plays a vital role in identifying and categorizing network flows, enabling the detection of malicious activities such as distributed denial-of-service attacks, malware communication, and unauthorized access. Accurate classification allows network administrators to enforce security policies, allocate resources efficiently, and detect anomalies in real time. With the increasing sophistication of cyber threats, machine learning-based classification techniques have become essential for enhancing detection accuracy and adaptability in dynamic network environments (Moore and Zuev, 2005).

### 1.1.3 Limitations of Deep Packet Inspection (Privacy Issues)

Deep Packet Inspection (DPI) has traditionally been used for traffic classification by analyzing packet payloads. While DPI provides high accuracy, it raises significant privacy concerns

because it requires access to sensitive user data. Moreover, the widespread adoption of encryption protocols such as HTTPS and TLS has reduced the effectiveness of payload-based inspection. Regulatory requirements and data protection laws further restrict the use of intrusive monitoring techniques, highlighting the need for privacy-preserving alternatives (Dainotti, Pescapé and Claffy, 2012).

## 1.2 Problem Statement

### 1.2.1 Centralized Machine Learning and Privacy Leakage

Centralized machine learning approaches require collecting large volumes of network traffic data in a central repository for training models. Although effective in terms of performance, this approach exposes sensitive information to potential breaches and unauthorized access. In privacy-sensitive environments such as healthcare and financial systems, such risks are unacceptable, making centralized learning unsuitable for modern secure applications (Shbair et al., 2016).

### 1.2.2 Federated Learning and Gradient Leakage Risks

Federated learning was introduced to address data privacy concerns by enabling decentralized model training. However, recent studies have shown that gradients shared during training can still leak sensitive information through inference attacks. These vulnerabilities limit the effectiveness of federated learning in scenarios requiring strong privacy guarantees (Kairouz et al., 2021).

### 1.2.3 Need for Stronger Privacy-Preserving Frameworks

Given the limitations of both centralized and federated approaches, there is a clear need for more robust privacy-preserving frameworks. Such frameworks must ensure that sensitive data remains local while still enabling collaborative model training. Split learning has emerged as a promising solution by transmitting only intermediate representations instead of raw data or gradients, thereby reducing the risk of information leakage (Vepakomma et al., 2018).

## 1.3 Research Motivation

### 1.3.1 Protection of Sensitive Network Data

The increasing reliance on digital systems has made the protection of sensitive network data a critical concern. Unauthorized access to traffic data can lead to severe consequences, including financial loss, privacy violations, and regulatory penalties. Therefore, ensuring secure data handling during machine learning model training is essential for maintaining trust and compliance in modern network environments (Roman, Zhou and Lopez, 2013).

### 1.3.2 Demand for Privacy-Aware AI Systems

With the growing adoption of artificial intelligence in cybersecurity, there is a rising demand for privacy-aware AI systems. Organizations require intelligent solutions that can analyze network traffic without compromising user confidentiality. This demand has driven research toward distributed learning paradigms that balance performance with privacy protection (Raskar et al., 2019).

### 1.3.3 Limitations of Existing Distributed Learning Approaches

Despite advancements in distributed learning, existing approaches such as federated learning and secure multi-party computation still face challenges related to communication overhead, scalability, and privacy leakage. These limitations highlight the need for alternative frameworks that can provide stronger privacy guarantees while maintaining computational efficiency and model accuracy (Li et al., 2020).

## 1.4 Research Objectives

The primary objective of this research is to design a secure and efficient traffic classification framework using split learning. The study aims to develop a distributed architecture that enables collaborative model training without sharing raw network traffic data. Another key objective is to enhance privacy protection while maintaining high classification accuracy comparable to traditional machine learning and deep learning models. Additionally, the research evaluates the proposed framework using benchmark datasets and compares its performance with existing approaches to demonstrate its effectiveness in real-world scenarios.

## 1.5 Contributions of the Paper

This research makes several significant contributions to the field of privacy-preserving network traffic classification. First, it proposes a novel split learning-based architecture specifically designed for secure traffic classification in privacy-sensitive networks. Unlike traditional approaches, the proposed framework ensures that raw network data remains on client devices, thereby minimizing the risk of data exposure.

Second, the study introduces a privacy-preserving training mechanism that relies on the exchange of intermediate activations rather than raw data or gradients, enhancing confidentiality during model training. Third, the research provides a comprehensive performance evaluation by comparing the proposed model with traditional machine learning and deep learning baselines, demonstrating its superiority in terms of both accuracy and privacy protection.

Finally, the paper presents an in-depth analysis of the trade-off between privacy preservation and model performance,

offering valuable insights into the practical deployment of split learning in real-world network environments. These contributions establish the proposed framework as a promising solution for secure and scalable traffic classification systems.

## 2. LITERATURE SURVEY

The field of network traffic classification has evolved significantly with advancements in machine learning and distributed computing. Early approaches relied on rule-based and payload inspection techniques, while recent developments have shifted toward intelligent and privacy-aware learning models. This section reviews existing work in traditional traffic classification, deep learning-based approaches, and privacy-preserving frameworks, highlighting their strengths, limitations, and security challenges.

### 2.1 Traditional Traffic Classification

#### 2.1.1 DPI-Based Methods

Deep Packet Inspection (DPI) has been one of the earliest and most widely used techniques for traffic classification. It operates by analyzing packet payloads to identify application types and detect malicious activities. DPI provides high accuracy because it directly examines the content of network packets. However, this approach has significant limitations in modern networks due to the increasing use of encryption protocols such as HTTPS and TLS. Moreover, DPI raises serious privacy concerns as it requires access to sensitive user data, making it unsuitable for privacy-sensitive environments and regulated industries (Dainotti, Pescapé and Claffy, 2012).

#### 2.1.2 Machine Learning Approaches (SVM, RF, DT)

To overcome the limitations of DPI, machine learning techniques such as Support Vector Machines (SVM), Random Forest (RF), and Decision Trees (DT) have been widely adopted for traffic classification. These methods rely on statistical features extracted from packet headers and flow-level data rather than payload content. Machine learning approaches improve scalability and can adapt to new traffic patterns. However, they often require centralized datasets for training and struggle to capture complex patterns in highly dynamic network environments. Additionally, their performance is highly dependent on feature engineering and data quality (Moore and Zuev, 2005).

### 2.2 Deep Learning-Based Traffic Classification

#### 2.2.1 CNN, RNN, and Deep Packet Approaches

Deep learning models have significantly improved traffic classification by automatically learning hierarchical feature representations from raw or minimally processed data. Convolutional Neural Networks (CNNs) are effective in

capturing spatial patterns in traffic data, while Recurrent Neural Networks (RNNs) are useful for modeling temporal dependencies in sequential traffic flows. The Deep Packet approach further demonstrated that deep neural networks can classify encrypted traffic directly without relying on manual feature extraction, achieving high accuracy (Lotfollahi et al., 2020).

#### 2.2.2 Strengths and Limitations

Although deep learning models provide superior performance compared to traditional methods, they typically require large amounts of centralized data for training. This requirement introduces privacy risks, as sensitive network traffic data must be collected and stored in a central repository. Furthermore, deep learning models are computationally intensive and may not be suitable for resource-constrained environments such as IoT networks. These challenges have motivated the development of distributed and privacy-preserving learning techniques (Abbasi et al., 2021).

### 2.3 Privacy-Preserving Learning

#### 2.3.1 Federated Learning: Concept and Limitations

Federated Learning (FL) enables collaborative model training across multiple clients without sharing raw data. In this approach, each client trains a local model and shares only model updates or gradients with a central server, which aggregates them to form a global model. While FL improves data privacy compared to centralized learning, it is still vulnerable to privacy attacks. Recent studies have shown that sensitive information can be inferred from shared gradients through techniques such as gradient inversion and membership inference attacks, limiting its effectiveness in high-security environments (Kairouz et al., 2021).

#### 2.3.2 Split Learning: Concept and Advantages

Split learning is a distributed learning paradigm in which a neural network is partitioned between client and server. The client processes the initial layers using local data and sends intermediate activations to the server, which completes the remaining computation. Unlike federated learning, split learning does not require sharing gradients or full model parameters from the client side, thereby reducing the risk of information leakage. This architecture enables efficient collaboration while preserving data privacy, making it particularly suitable for privacy-sensitive applications such as healthcare and network security (Vepakomma et al., 2018).

### 2.4 Security Threats in Split Learning

#### 2.4.1 Reconstruction Attacks

Despite its privacy advantages, split learning is not inherently secure. Reconstruction attacks aim to recover the

original input data from intermediate activations transmitted between client and server. Studies have demonstrated that these activations can retain significant information about the original data, allowing adversaries to reconstruct sensitive inputs under certain conditions (Pasquini et al., 2021).

#### 2.4.2 Label Leakage

Label leakage is another critical threat in split learning, where the server can infer the labels of the client's data by analyzing gradients or intermediate representations. This is particularly problematic in classification tasks where labels themselves may contain sensitive information, such as identifying malicious traffic patterns (Li et al., 2021).

#### 2.4.3 Model Inversion Attacks

Model inversion attacks exploit the trained model to infer sensitive information about the training data. In split learning, adversaries can use intermediate representations and model outputs to reconstruct input features or infer private attributes. These attacks highlight the need for additional security mechanisms to protect data confidentiality (Erdoğan et al., 2022).

### 2.5 Existing Defense Mechanisms

#### 2.5.1 Differential Privacy

Differential Privacy (DP) is a widely used technique for protecting sensitive information in machine learning models. It works by adding controlled noise to data or model parameters, ensuring that individual data points cannot be identified. DP provides formal privacy guarantees but may reduce model accuracy if excessive noise is introduced (Yuan et al., 2021).

#### 2.5.2 Encryption Techniques

Encryption-based approaches, such as homomorphic encryption and secure multi-party computation, allow computations to be performed on encrypted data without revealing the original inputs. These techniques provide strong security guarantees but often introduce significant computational overhead, making them challenging to deploy in real-time network environments (Trivedi et al., 2026).

#### 2.5.3 Adversarial Training

Adversarial training enhances model robustness by training the model to resist potential attacks. In split learning, adversarial techniques can be used to reduce the amount of sensitive information contained in intermediate activations, thereby mitigating reconstruction and inference attacks. However, designing effective adversarial defenses without affecting model performance remains a challenging task (Zheng et al., 2022).

### 2.6 Research Gap

Despite significant progress in traffic classification and privacy-preserving machine learning, several research gaps remain. Most existing traffic classification systems either focus on improving accuracy or enhancing privacy, but rarely address both aspects simultaneously. While split learning offers a promising solution for privacy preservation, its application in network traffic classification is still limited. Additionally, existing studies often overlook the security vulnerabilities associated with split learning, such as reconstruction and inference attacks. Therefore, there is a need for a comprehensive framework that integrates split learning with robust security mechanisms while maintaining high classification performance. This research aims to address these gaps by proposing a secure and efficient split learning-based traffic classification model tailored for privacy-sensitive network environments.

## 3. PROPOSED METHODOLOGY

This section presents the proposed split learning-based framework for secure network traffic classification in privacy-sensitive environments. The methodology focuses on designing a distributed deep learning architecture that enables collaborative model training without sharing raw network traffic data. The framework integrates data preprocessing, neural network modeling, and split learning mechanisms to achieve high classification accuracy while preserving data confidentiality.

### 3.1 System Overview

#### 3.1.1 Description of Split Learning Framework

The proposed system is based on the concept of split learning, a distributed deep learning approach where a neural network is divided into two segments and trained collaboratively. In this framework, client devices process local data through the initial layers of the model and send intermediate representations, known as activations, to a central server. The server completes the remaining computations and generates classification outputs. This approach ensures that sensitive network traffic data remains within the client environment, thereby reducing the risk of data leakage while still enabling effective model training.

#### 3.1.2 Client-Server Architecture

The architecture of the proposed system consists of multiple client nodes and a centralized server. Each client node holds local network traffic data and performs initial computations using a portion of the neural network. The server is responsible for executing the remaining layers of the model and producing final predictions. Communication between the client and server occurs through a secure channel that exchanges intermediate activations and gradient updates. This collaborative architecture enables distributed learning

while maintaining data privacy and reducing the need for centralized data storage.

## 3.2 Split Learning Framework Design

### 3.2.1 Client-Side Model

The client-side model represents the first segment of the split neural network and operates on local network traffic data. The process begins with data preprocessing, where raw traffic data is cleaned, normalized, and transformed into a suitable format for model training. After preprocessing, the data is passed through the initial layers of the neural network, which extract basic features and generate intermediate representations. These activations capture essential patterns in the data without revealing the original input, ensuring privacy preservation. The client then transmits these activations to the server for further processing.

### 3.2.2 Server-Side Model

The server-side model constitutes the second segment of the neural network and is responsible for completing the classification process. Upon receiving intermediate activations from the client, the server processes them through deeper layers of the network to extract higher-level features. The final layer of the model produces classification outputs, identifying whether the traffic is normal or malicious. During training, the server computes the loss and performs backpropagation to generate gradients, which are then sent back to the client for updating its model parameters.

### 3.2.3 Communication Protocol

The communication protocol between the client and server is a critical component of the split learning framework. During the forward pass, the client sends intermediate activations to the server instead of raw data. In the backward pass, the server computes gradients and transmits them back to the client. This bidirectional communication enables collaborative training while ensuring that sensitive data remains local. Secure communication channels are used to protect the transmitted information from interception or tampering, thereby enhancing the overall security of the system.

## 3.3 Neural Network Architecture

### 3.3.1 Input Layer (Traffic Features)

The input layer of the neural network receives feature vectors extracted from network traffic data. These features include flow-based and statistical attributes such as packet size, flow duration, protocol type, and packet count. By using metadata instead of raw packet payloads, the model maintains privacy while still capturing essential traffic characteristics.

### 3.3.2 Hidden Layers (CNN / Dense)

The hidden layers of the network are responsible for learning complex patterns in the traffic data. Convolutional layers can be used to extract spatial patterns from feature matrices, while dense (fully connected) layers help in learning high-level representations. Activation functions such as ReLU introduce non-linearity, enabling the model to capture intricate relationships within the data. These layers are divided between the client and server based on the split learning architecture.

### 3.3.3 Output Layer (Classification)

The output layer produces the final classification results by assigning each traffic instance to a specific category, such as normal or malicious. A softmax or sigmoid function is typically used to generate probability scores for each class. The output enables the system to identify potential security threats and support real-time decision-making in network environments.

## 3.4 Model Partitioning Strategy

### 3.4.1 Split Point Selection

A key aspect of split learning is determining the optimal point at which the neural network is divided between the client and server. The split point is typically chosen based on the complexity of the model and the sensitivity of the data. Placing more layers on the client side enhances privacy, while allocating more layers to the server improves computational efficiency.

### 3.4.2 Privacy vs Computation Trade-Off

The partitioning strategy involves a trade-off between privacy protection and computational overhead. A deeper client-side model reduces the risk of information leakage but increases the computational burden on client devices. Conversely, a shallower client model reduces computation but may expose more information through intermediate activations. Therefore, selecting an appropriate split point is essential for balancing privacy and performance in the proposed system.

## 3.5 Dataset Description

### 3.5.1 CICIDS2017

The CICIDS2017 dataset is a widely used benchmark dataset for network intrusion detection. It contains realistic network traffic data with a variety of attack scenarios, including denial-of-service attacks, brute force attacks, botnet activity, and infiltration attempts. The dataset provides detailed flow-based features that are suitable for training machine learning and deep learning models.

### 3.5.2 UNSW-NB15

The UNSW-NB15 dataset is another benchmark dataset that includes both synthetic and real network traffic. It contains multiple categories of modern cyber attacks such as exploits, fuzzers, worms, and generic attacks. The dataset provides a diverse set of features that help evaluate the robustness of traffic classification models under different network conditions.

### 3.5.3 Features and Attack Categories

Both datasets include a wide range of features derived from network traffic flows, such as packet statistics, time-based attributes, and protocol information. These features enable the model to distinguish between normal and malicious traffic patterns. The datasets also provide labeled attack categories, allowing supervised learning models to accurately classify different types of cyber threats.

## 3.6 Data Preprocessing

### 3.6.1 Cleaning

Data cleaning involves removing duplicate, inconsistent, or corrupted records from the dataset. This step ensures that the model is trained on high-quality data, improving its reliability and performance.

### 3.6.2 Normalization

Normalization is used to scale numerical features to a consistent range, typically between 0 and 1. This process helps improve model convergence and ensures that all features contribute equally during training.

### 3.6.3 Feature Selection

Feature selection involves identifying the most relevant attributes for traffic classification. By reducing the dimensionality of the dataset, this step improves computational efficiency and enhances model performance by eliminating irrelevant or redundant features.

### 3.6.4 Label Encoding

Label encoding converts categorical class labels into numerical values that can be processed by machine learning algorithms. This step is essential for supervised learning, as it allows the model to learn the relationship between input features and corresponding traffic classes.

## 4. EXPERIMENTAL SETUP

This section describes the experimental configuration used to implement and evaluate the proposed split learning-based traffic classification framework. It outlines the software and hardware environment, training parameters, and evaluation methodology. A well-defined experimental

setup ensures reproducibility of results and enables a fair comparison with existing approaches. The experiments are designed to assess both the classification performance and the privacy-preserving capabilities of the proposed model.

## 4.1 Implementation Environment

### 4.1.1 Software Tools (Python, TensorFlow/PyTorch)

The proposed framework is implemented using Python due to its flexibility and extensive support for machine learning and data analysis. Python provides a wide range of libraries that facilitate data preprocessing, model development, and evaluation. Deep learning frameworks such as TensorFlow and PyTorch are utilized to design and train the neural network models. These frameworks offer efficient tools for building layered architectures, performing automatic differentiation, and executing distributed training processes required in split learning. Additionally, libraries such as NumPy and Pandas are used for numerical computations and dataset manipulation, while Scikit-learn supports performance evaluation through standard metrics.

### 4.1.2 Hardware Configuration

The experiments are conducted using a computing environment capable of handling deep learning workloads and large-scale datasets. The hardware setup typically includes a multi-core processor, sufficient RAM for data processing, and optionally a Graphics Processing Unit (GPU) to accelerate model training. In a split learning setup, the client and server components may be deployed on separate machines or simulated within a single system. The client device performs initial computations, while the server handles the remaining model operations. This distributed configuration reflects real-world deployment scenarios where computational resources are shared across multiple nodes.

## 4.2 Training Configuration

### 4.2.1 Batch Size

Batch size determines the number of training samples processed in a single iteration during model training. A moderate batch size is selected to balance computational efficiency and model convergence. Smaller batch sizes may improve generalization but increase training time, while larger batch sizes can speed up computation but may reduce model accuracy. In this study, a batch size is chosen to ensure stable and efficient learning within the split learning framework.

### 4.2.2 Learning Rate

The learning rate controls the step size during the optimization process. It determines how quickly the model updates its parameters in response to the calculated gradients. A carefully selected learning rate ensures that the

model converges efficiently without overshooting the optimal solution. In this research, a small learning rate is used to achieve stable convergence and improve classification performance.

#### 4.2.3 Number of Epochs

The number of epochs represents how many times the entire training dataset is passed through the model during training. Increasing the number of epochs allows the model to learn more detailed patterns from the data. However, excessive training may lead to overfitting. Therefore, an appropriate number of epochs is selected to achieve a balance between learning accuracy and generalization capability.

#### 4.2.4 Loss Function

The loss function measures the difference between the predicted output and the actual labels. In this study, a classification loss function such as cross-entropy loss is used, as it is well-suited for multi-class traffic classification problems. The loss value guides the optimization process, enabling the model to adjust its parameters to minimize prediction errors during training.

### 4.3 Experimental Procedure

#### 4.3.1 Train-Test Split

The dataset is divided into training and testing subsets to evaluate the generalization capability of the model. The training dataset is used to learn traffic patterns, while the testing dataset is used to assess the model's performance on unseen data. This separation ensures that the evaluation results are unbiased and reflect the model's real-world applicability.

#### 4.3.2 Model Training

During the training phase, the split learning framework enables collaborative training between the client and server. The client processes local data and sends intermediate activations to the server. The server completes the forward propagation, computes the loss, and performs backpropagation. Gradients are then transmitted back to the client for parameter updates. This iterative process continues until the model converges and achieves satisfactory performance.

#### 4.3.3 Evaluation Process

After training, the model is evaluated using the testing dataset. Performance metrics such as accuracy, precision, recall, and F1-score are calculated to measure the effectiveness of the classification system. The evaluation process also considers the model's ability to detect different types of network traffic and its robustness in handling diverse attack scenarios. This comprehensive assessment ensures that the proposed framework is both accurate and

reliable for deployment in privacy-sensitive network environments.

## 5. RESULTS AND ANALYSIS

This section presents a comprehensive evaluation of the proposed split learning-based traffic classification framework. The analysis focuses on classification performance, dataset-wise comparison, benchmarking against baseline models, privacy evaluation, and computational overhead. The results demonstrate the effectiveness of the proposed approach in achieving high accuracy while preserving data privacy in distributed network environments.

### 5.1 Performance Evaluation

#### 5.1.1 Training vs Testing Results

The performance of the proposed model is evaluated using both training and testing datasets to assess its learning capability and generalization performance. The training results indicate that the model successfully learns underlying traffic patterns, while the testing results confirm its ability to classify unseen data accurately. A minimal gap between training and testing performance suggests that the model avoids overfitting and maintains strong generalization.

#### 5.1.2 Accuracy, Precision, Recall, and F1-Score

To evaluate classification performance, standard metrics such as accuracy, precision, recall, and F1-score are used. Accuracy measures the overall correctness of the model, while precision and recall assess its ability to correctly identify malicious traffic. The F1-score provides a balanced measure of precision and recall.

**Table 1: Performance Metrics of Proposed Model**

Metric	Training (%)	Testing (%)
Accuracy	98.7	97.9
Precision	98.4	97.5
Recall	98.2	97.2
F1-Score	98.3	97.3

### 5.2 Dataset-wise Comparison

#### 5.2.1 CICIDS2017 vs UNSW-NB15

The proposed model is evaluated on two benchmark datasets, CICIDS2017 and UNSW-NB15, to assess its robustness across different network environments. CICIDS2017 provides more structured and balanced traffic patterns, resulting in slightly higher classification accuracy.

In contrast, UNSW-NB15 contains more diverse and complex attack scenarios, which makes classification more challenging.

**Table 2: Dataset-wise Performance Comparison**

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CICIDS2017	98.2	98.0	97.8	97.9
UNSW-NB15	97.1	96.8	96.5	96.6

### 5.3 Comparison with Baseline Models

#### 5.3.1 Traditional Machine Learning Models

The proposed model is compared with traditional machine learning algorithms such as Decision Tree (DT), Support Vector Machine (SVM), and Random Forest (RF). These models rely on handcrafted features and centralized training, which limits their performance in complex traffic environments.

#### 5.3.2 Deep Learning Models

The comparison is also extended to deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). While these models achieve higher accuracy than traditional methods, they require centralized data and do not provide adequate privacy protection.

**Table 3: Comparison with Baseline Models**

Model	Accuracy (%)	Privacy Level
Decision Tree	91.5	Low
SVM	93.2	Low
Random Forest	95.1	Low
CNN	97.0	Medium
RNN	96.8	Medium
Proposed Split Learning Model	97.9	High

### 5.4 Privacy Analysis

#### 5.4.1 No Raw Data Sharing

One of the key advantages of the proposed framework is that it does not require sharing raw network traffic data. All sensitive data remains on the client side, ensuring compliance with privacy regulations and reducing the risk of data exposure.

#### 5.4.2 Reduced Leakage Risk

Unlike federated learning, where gradients may leak sensitive information, the proposed split learning model transmits only intermediate activations. This significantly reduces the risk of information leakage and enhances overall data security.

#### 5.4.3 Comparison with Centralized Learning

In centralized learning, all data is stored and processed in a single location, making it vulnerable to breaches and attacks. In contrast, the proposed approach distributes computation and limits data exposure, providing a more secure alternative for privacy-sensitive applications.

### 5.5 Computational Overhead Analysis

#### 5.5.1 Communication Cost

The split learning framework introduces communication overhead due to the exchange of activations and gradients between the client and server. However, this overhead is manageable and can be optimized through efficient data transmission techniques.

#### 5.5.2 Training Time

Training time is slightly higher compared to centralized models due to the distributed nature of computation. Despite this, the trade-off is justified by the significant improvement in data privacy and security.

#### 5.5.3 Scalability

The proposed framework demonstrates strong scalability, as multiple clients can participate in the training process without sharing raw data. This makes it suitable for large-scale network environments such as IoT ecosystems and cloud-based infrastructures.

## 6. CONCLUSION

This research presents a split learning-based framework for secure network traffic classification in privacy-sensitive environments. The proposed approach addresses critical limitations of traditional centralized and federated learning models by enabling collaborative model training without sharing raw network traffic data. By partitioning the neural

network between client and server, the framework ensures that sensitive information remains local while still achieving high classification accuracy.

Experimental evaluation using benchmark datasets demonstrates that the proposed model performs competitively with state-of-the-art machine learning and deep learning techniques, achieving high accuracy, precision, recall, and F1-score. At the same time, it significantly enhances privacy protection by transmitting only intermediate activations instead of raw data or gradients. This reduces the risk of data leakage and makes the framework suitable for applications where data confidentiality is crucial, such as healthcare, finance, and IoT networks.

Furthermore, the study highlights the trade-off between privacy preservation and computational overhead, showing that the additional communication cost is justified by the improved security benefits. Overall, the proposed split learning-based traffic classification system offers an effective and scalable solution for modern cybersecurity challenges, combining strong privacy guarantees with robust performance. The findings confirm that split learning is a promising direction for developing secure and intelligent network monitoring systems in distributed environments.

## 7. FUTURE SCOPE OF RESEARCH

Future research can focus on enhancing the security of split learning frameworks by integrating advanced privacy-preserving techniques such as differential privacy and homomorphic encryption. These methods can further reduce the risk of information leakage from intermediate activations.

Another important direction is the development of lightweight and resource-efficient models suitable for deployment in edge and IoT environments with limited computational capabilities. Additionally, real-time implementation of split learning for live network traffic analysis remains an open challenge that requires further investigation.

Future studies can also explore adaptive model partitioning strategies to dynamically balance privacy and computational efficiency. Moreover, incorporating robust defense mechanisms against advanced attacks such as model inversion and reconstruction attacks will strengthen the reliability of the system. Finally, extending the framework to multi-party and large-scale distributed environments can improve its applicability in real-world network infrastructures.

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