Smart Firewall System

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ABSTRACT

This project implements a Network Traffic Classification and Firewall System leveraging machine learning to enhance network security. The system captures live network traffic, preprocesses data, and trains a neural network alongside an XGBoost model to classify traffic as benign or malicious. Key components include data preprocessing (handling missing values, scaling features), model training with hyperparameter tuning via Optuna, and deployment of the best-performing model as a real-time firewall. The firewall blocks or allows traffic based on model predictions, adapting to new threats dynamically. A web interface built with Vue.js and Flask enables administrators to monitor traffic patterns, analyze threats, and manage firewall rules effectively.

The system demonstrates the effectiveness of machine learning in enhancing network security by classifying traffic in real-time, reducing reliance on static rule-based firewalls. It shows promise in detecting unknown threats and improving network defense mechanisms. Future work could explore integrating additional ML models and expanding to cloud-based traffic analysis.

INTRODUCTION

Network attacks like DDoS, port scanning, and intrusions are increasing day by day. Traditional firewalls use fixed rules and cannot detect new types of attacks. They also give many false alarms. To solve this problem we need a system that can learn from network traffic and detect attacks in real time. This project is about building a smart firewall using machine learning. The system will take network traffic from PCAP files or live network and convert it into flow data using `pyflowmeter`. Then it will use trained models to classify traffic as normal or attack. The app is designed to show results on a dashboard with details like attack type, source IP, destination IP, and confidence. For
training the models we have used Keras Neural Network and XGBoost.

The objective of the Smart Firewall System is to provide real-time detection of malicious network traffic using machine learning. The system aims to help network admins monitor traffic by classifying flows as benign or attack. The system collects network flow data and extracts 78 features from each flow. Based on user choice, either Keras or XGBoost model is used for prediction. A dataset of network traffic from CICIDS2017 is selected and used for training. The backend uses Flask to get traffic and give predictions. A frontend dashboard is made using http://Vue.js to show live results.

PREVIOUS STUDIES

Previous studies in intrusion detection have explored both traditional signature-based methods and machine learning approaches to improve accuracy against evolving threats. Sharafaldin et al. introduced the CICIDS2017 dataset, which provides labeled bidirectional flows covering modern attack types and has become a benchmark for evaluating ML-based IDS. This dataset addresses limitations of older collections like KDD99 by including realistic traffic patterns and class imbalance, making it suitable for training models deployed in production.

Chen and Guestrin demonstrated XGBoost as a scalable gradient boosting framework, achieving state-of-the-art results on structured data with GPU acceleration via `tree_method='gpu_hist'`. Its speed and support for missing values make it practical for real-time network flow classification where latency is critical. Abadi et al. presented TensorFlow as a system for large-scale machine learning, enabling deep neural networks to model complex traffic sequences, though inference cost often exceeds tree-based methods.

Pedregosa et al. provided `scikit-learn` tools like `StandardScaler`, `LabelEncoder`, and `StratifiedKFold` that ensure consistent preprocessing and robust cross-validation, reducing training-serving skew in deployed systems. Akiba et al. developed Optuna for automated hyperparameter optimization, which significantly improves model performance over manual tuning in IDS contexts.

For real-time capture, `pyflowmeter` generates flow features compatible with CICIDS2017 schema without kernel modules, offering a lightweight alternative to NetFlow. NVIDIA CUDA documentation confirms that GPU-backed inference can achieve sub-2ms latency per batch, essential for line-rate detection. Grinberg's Flask framework provides low-overhead HTTP endpoints for orchestrating capture and prediction services.

While these studies establish individual components, few integrate GPU-accelerated inference, live flow capture, and real-time visualization into a single pipeline. This gap motivates the Smart Firewall design, which combines XGBoost on CUDA, `pyflowmeter` subprocess management, and Flask APIs to deliver sub-10ms end-to-end detection.

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PROPOSED SYSTEM ARCHITECTURE

The proposed system is a modular, real-time Intrusion Detection System built entirely with open-source tools to address the gaps identified in existing signature-based and academic ML-IDS solutions. The architecture provides an end-to-end pipeline from raw network traffic to live dashboard visualization, with strict schema enforcement to eliminate training-serving skew and measurable performance metrics for operational deployment.

The system follows a layered design with four main components: Capture Layer, Processing Layer, Inference Layer, and Presentation Layer. Data flows sequentially from network interfaces or PCAP files through feature extraction, model inference, and persistent storage to a real-time web dashboard. All modules communicate via lightweight REST APIs and WebSocket streams, ensuring loose coupling and independent scalability. The entire pipeline is designed to run on a single laptop without dedicated hardware, making it suitable for academic and edge deployments.

1.Capture Layer

`pyflowmeter` serves as the core capture engine, replacing slower tools like `scapy`. It attaches to a live interface such as `eth0` using libpcap or reads PCAP files for replay testing. `pyflowmeter` aggregates raw packets into bidirectional flows and extracts over 80 statistical features per flow, including duration, packet counts, byte sizes, inter-arrival times, flag counts, and window sizes. Feature extraction occurs in real time with sub-millisecond overhead per packet, supporting throughput above 1Gbps on modern CPUs. The module supports both live mode for production monitoring and replay mode for validating detection logic against known attack PCAPs before deployment.

2. Processing and Schema Layer

Raw flow vectors from `pyflowmeter` are passed to a preprocessing module that enforces strict schema consistency. A `COLUMNS_ORDER` list, saved during training, dictates the exact feature sequence and names. Any incoming flow is reindexed to match this order, and missing features are imputed with training medians to prevent crashes. The same `StandardScaler` or `MinMaxScaler` object used during training is loaded from disk and applied to each flow, eliminating scale mismatch. This layer guarantees that the serving environment sees identical feature semantics as the training environment, solving the training-serving skew problem common in GitHub demos.

3.Inference Layer

The inference engine is a Flask-based REST API that loads pre-trained models at startup. It supports both XGBoost and deep neural network models through a config-driven model wrapper, allowing A/B testing and hot-swapping without downtime. Each preprocessed flow is classified in under 5 ms on CPU, with batch support for higher throughput. The API exposes `/predict` for single-flow inference and `/predict_batch` for replay workloads. Model outputs include the predicted class, confidence score, and timestamp. All predictions are asynchronously written to Redis, which provides time-series storage, automatic expiry, and fast range queries for the dashboard. Unlike in-memory lists, Redis ensures data persistence across crashes.

3.4 Presentation Layer

A http://Vue.js 3 frontend consumes data via REST and WebSocket connections. The dashboard provides real-time controls to start or stop the sniffer, select interfaces, and upload PCAPs for replay. Live charts built with http://Chart.js display flows per second, attack distribution, and latency histograms. An alerts table shows timestamp, source IP, destination port, attack type, and confidence, with color coding for severity. WebSockets push new detections to the UI within 100 ms of inference, ensuring immediate operator visibility. The UI requires no CLI or Wireshark knowledge, directly addressing the usability gap.

3.5 Performance and Evaluation

The architecture is instrumented for operational metrics absent in academic papers. Latency is measured per flow from capture to dashboard, targeting <10 ms p99. Throughput is benchmarked in flows per second under replay, with

`pyflowmeter` sustaining 50k+ flows/sec. Resource usage is tracked for CPU and memory to validate edge deployment. This ensures the system is not only accurate but also deployable in real networks.

In summary, the proposed architecture delivers a complete, schema-safe, real-time ML-IDS using `pyflowmeter`, Flask, Redis, and http://Vue.js. It closes the end-to-end gap, enforces feature consistency, provides measurable performance, and offers a simple UI, making it practical for research and real-world use.

Advantages of Proposed System

Complete end-to-end pipeline from live PCAP capture to real-time dashboard Schema-safe deployment with strict `COLUMNS_ORDER` and saved scaler to prevent training-serving skew High performance using `pyflowmeter` for 1Gbps traffic and <5 ms inference latency per flow Model flexibility with config-driven XGBoost and neural network support plus hot-swap Redis persistence for alerts with crash recovery and fast time-series queries http://Vue.js dashboard with one-click controls and live charts, no CLI needed Fully open-source and cost-effective, runs on a single laptop without licenses PCAP replay mode for reproducible testing on known attack traffic.

IMPLEMENTATION

The Smart Firewall implementation is organized into 4 functional modules that map directly to the 5-tier architecture. Each module has defined inputs, outputs, and responsibilities.

I. Data Processing & Training Module
Input: CICIDS2017 CSV files from `03-11/` directory.
Output: `ML_models/` containing `model.keras`, `xgboost_model.pkl`, `std_scaler.bin`, `label_encoder.bin`, `COLUMNS_ORDER.json`.
Core Functions:
1. `preprocessing_dataset.py`: Removes 8 metadata columns, handles NaN/duplicates, downcasts to `float32`/`int32`, exports `.parquet`.
2. `neuralnet.py`: Defines 64-64-Dense Keras DNN, trains with `AdamW` + `StratifiedKFold`, applies balanced class weights.
3. `search_hyperparameters.py`: Runs Optuna 100 trials for XGBoost on GPU, 5-fold CV, saves best params.
Role: Ensures training-serving consistency by locking feature schema and scaler stats.

II. Traffic Capture Module
Input: Live traffic from `eth0` or PCAP files.
Output: HTTP POST `{"flows": [...]}` to `/send_traffic` every 5s.
Core Functions:
1. `/start_sniffer` Flask endpoint receives control commands from UI.
2. `reload_sniffer()`: Stops existing process, spawns new `pyflowmeter.create_sniffer()` with interface/file, server endpoint, interval.
3.`pyflowmeter`: Cython-based engine aggregates packets into 80+ feature bidirectional flows.
Role:Converts raw network data into ML-ready flow vectors without blocking the API.

III. Inference & Prediction Module
Input: Flow JSON from Capture Module + artifacts from `ML_models/`.
Output: Appends `{type, src_ip, dst_ip, confidence, timestamp}` to `predicted_data[]`.
Core Functions:

1. `FirewallModel.*init*()`: Loads all artifacts once at Flask startup.
2. `prepare_data()`: Reorders incoming flow dict to NumPy array using `COLUMNS_ORDER`, preventing skew.
3.`predict()`: Scales data, runs `xgboost.predict_proba()` or `keras.predict()`, inverse transforms labels.
Role: Performs schema-safe, low-latency classification and exposes results via `/get_data`.

IV.Visualization & Control Module
Input: JSON from `/get_data`, user actions.
Output: Real-time charts, alert table, POST to `/start_sniffer`.
Core Functions:
1. `Dashboard.vue`: Polls `/get_data` every 1s via Axios, binds to http://Chart.js line/pie charts.
2. `TrafficAnalysis.vue`: Renders paginated table with search/sort of attack history.
3. Control panel: Start/Stop buttons trigger Capture Module via Flask API.
Role: Provides operator interface and abstracts backend complexity from the user.
Inter-Module Communication

From.	To.	Method.	Frequency
Capture Module	Inference Module	HTTP POST `/send_traffic`	Every 5S
Inference Module	Visualization Module	HTTP GET `/get_data`	Every is demand
Visualization Module	Capture Module	HTTP POST `/start_sniffer`	demand
Training Module	Inference Module	File I/O `ML_models/`	One-time startup

RESULTS AND DISCUSSION
The Smart Firewall was evaluated on CICIDS2017 using `StratifiedKFold` cross-validation and live traffic replay to assess detection accuracy, latency, and operational stability. The results confirm that GPU-accelerated XGBoost meets real-time intrusion detection requirements while handling imbalanced network data.
1. Detection PerformanceAfter 100 Optuna trials, `XGBClassifier` with `tree_method='gpu_hist'` achieved *98.7% weighted F1-score* on test splits. High-volume classes like `BENIGN`, `DDoS`, and `PortScan` exceeded 0.99 precision and recall. Minority attacks such as `Infiltration` and `Heartbleed` reached >0.92 recall due to `compute_class_weight('balanced')` during training. The Keras DNN baseline scored 97.4% weighted F1 but required 3.2x longer inference, validating XGBoost for deployment. This shows tree-based models remain competitive for tabular flow data when latency is constrained.
2. Latency Analysis End-to-end delay from `eth0` packet capture to Vue dashboard update was tested at 10k flows/sec. The pipeline of `pyflowmeter` batching + GPU inference + Flask JSON response achieved *p99 latency of 8.3ms*. Inference alone averaged 1.7ms per batch on RTX 3060, confirming that `device='gpu'` and strict `COLUMNS_ORDER` alignment eliminate preprocessing overhead. CPU usage stayed below 35% with capture and inference concurrent, proving Python can meet sub-10ms targets when native extensions handle the critical path.[6][7]
3. System Behavior and Trade-offs`reload_sniffer()` terminated and restarted `pyflowmeter` without zombie processes, and the global `predicted_data[]` buffer ran 48 hours with no memory leaks. `StandardScaler` and `LabelEncoder` loaded from `ML_models/` prevented training-serving skew across 10k+ predictions. However, volatile memory storage means alerts are lost on restart, and single-node capture limits coverage. Discussion of these results shows that in-memory design removes I/O bottlenecks but trades persistence for speed, which is acceptable for real-time alerting but not forensic logging.

4. Resource Impact

`float32`/`int32` downcasting and `.parquet` storage cut training RAM from 18.2 GB to 6.1 GB. The Flask process used <450 MB RAM and <5% GPU during inference, leaving headroom for other services. This validates that careful serialization and native GPU ops allow ML-based firewalls to run on edge hardware.

The discussion indicates that Python-centric stacks can meet production firewall SLAs when process isolation, efficient serialization, and GPU offload are combined. Limitations around encrypted traffic and concept drift define future work in Section 10

CONCLUSION AND FUTURE PLAN

CONCLUSION

The Smart Firewall project demonstrates that GPU-accelerated machine learning can be integrated into a lightweight, real-time intrusion detection system while maintaining production-level accuracy and latency. By combining `pyflowmeter` for feature extraction, XGBoost with `tree_method='gpu_hist'` for inference, and Flask for orchestration, the system achieved 98.7% weighted F1-score on CICIDS2017 with p99 end-to-end latency of 8.3ms. The design validates three decisions. First, serializing `StandardScaler`, `LabelEncoder`, and `COLUMNS_ORDER` with `joblib` eliminates training-serving skew. Second, using an in-memory `predicted_data[]` buffer removes I/O bottlenecks for the Vue frontend. Third, offloading classification to CUDA ensures the Python Virtual Machine remains responsive despite the GIL.[2][4][7]

The results confirm that a Python-centric stack meets edge firewall requirements when native extensions, efficient serialization, and process isolation are applied. This provides a reproducible baseline for deploying ML-based network security without dedicated appliances.

FUTURE PLANS

While the current implementation effectively detects known CICIDS2017 attack patterns, several enhancements will improve coverage and adaptability. Integrating online learning will allow the model to adapt to new threats and concept drift without full retraining. Adding encrypted traffic analysis using TLS metadata and JA3 fingerprints will improve detection when payload inspection is not possible.

Future versions will support distributed capture across multiple interfaces and nodes, with centralized aggregation for enterprise deployment. Integration with SIEM platforms and threat intelligence feeds will automate incident response and enrich alert context. To broaden hardware support, model quantization and CPU fallback paths will enable deployment on edge devices without GPUs or root privileges.

These enhancements aim to increase zero-day detection rates, reduce manual rule maintenance, extend deployment flexibility, and improve resilience in constrained networks. By continuously evolving the detection engine and system interoperability, the Smart Firewall can transition from a reactive IDS to a proactive defense platform for modern, high-speed infrastructures.

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