© NOV 2025 | IRE Journals | Volume 9 Issue 5 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I5-1712370

AI-Driven Intelligent Firewall for Real-Time Intrusion Detection Using XGBoost and CIC-IDS-2017 Dataset

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Abstract- ***Network security remains a critical challenge due to increasingly sophisticated cyberattacks. Traditional firewalls employing static rules and signature-based detection prove ineffective against novel and evolving threats. This paper presents an artificial intelligence-driven intelligent firewall system capable of detecting multiple attack types in real-time using machine learning techniques. We preprocessed, cleaned, normalized, and merged network flow data from the CIC-IDS-2017 dataset, specifically utilizing Monday and Wednesday traffic captures. An XGBoost classifier was trained on extracted features, achieving enhanced accuracy in multi-class attack detection. A Flask-based web interface enables real-time CSV traffic prediction with immediate actionable results. The proposed system successfully identifies attacks including Port Scan, Distributed Denial of Service (DDoS), and Denial of Service (DoS) variants, producing labeled outputs for immediate firewall action. Experimental results demonstrate that machine learning-enhanced firewalls significantly outperform traditional rule-based systems in both adaptability and accuracy, validating their essential role in next-generation network security infrastructure.***

Index Terms ***Intrusion Detection System, Machine Learning, XGBoost, Network Security, CIC-IDS-2017, Cybersecurity***

I. INTRODUCTION

The proliferation of interconnected digital systems has fundamentally transformed modern society, yet this connectivity introduces unprecedented cybersecurity vulnerabilities. Contemporary networks face multifaceted threats including

Distributed Denial of Service (DDoS) attacks, port scanning reconnaissance, botnet infiltration, brute-force authentication attempts, and sophisticated application-layer exploits. These attacks have grown exponentially in both frequency and complexity, necessitating advanced defense mechanisms beyond traditional security paradigms.

Conventional perimeter firewalls operate on predetermined rule sets and signature-based detection mechanisms. While effective against known threats, these systems exhibit critical limitations when confronting novel attack vectors and zero-day exploits. The inherent rigidity of rule-based approaches cannot adapt to the dynamic threat landscape characterizing modern cyberattacks. This fundamental inadequacy motivates the integration of artificial intelligence and machine learning techniques into intrusion detection systems (IDS).

Machine Learning (ML) methodologies offer transformative capabilities for network security, including pattern recognition, anomaly detection, and efficient traffic classification. Among various ML algorithms, XGBoost (Extreme Gradient Boosting) has emerged as a highly efficient ensemble learning technique particularly suited for handling high-dimensional network flow datasets. Its capability to process complex feature interactions while maintaining computational efficiency makes it ideal for real-time intrusion detection applications.

This research presents the design, implementation, and evaluation of an AI-driven intelligent firewall system trained on the comprehensive CIC-IDS-2017 dataset. The system performs real-time prediction on uploaded network traffic CSV files, classifying each flow as either benign or representing a specific attack category.

Our primary contributions include:

1. Development of a robust preprocessing pipeline for multi-day network traffic data integration
2. Implementation of an XGBoost-based multi-class

classifier optimized for intrusion detection
3. Creation of a practical Flask-based web interface for real-time traffic analysis
4. Comprehensive evaluation demonstrating superiority over traditional rule-based approaches

The remainder of this paper is organized as follows: Section II reviews related work in ML-based intrusion detection. Section III details our methodology including dataset preparation and model development. Section IV presents the system architecture. Section V discusses experimental results. Section VI concludes with future research directions.

II. RELATED WORK

The application of machine learning to network intrusion detection has received substantial research attention over the past decade. This section reviews relevant literature establishing the foundation for our work.

A. Traditional Intrusion Detection Systems

Early IDS implementations relied primarily on signature-based detection and statistical anomaly identification. Denning [1] pioneered the concept of anomaly-based intrusion detection using statistical models. However, these approaches suffered from high false-positive rates and inability to detect novel attacks, motivating the exploration of machine learning alternatives.

B. Machine Learning for Intrusion Detection

Several researchers have demonstrated the efficacy of ML-based IDS systems. Buczak and Guven [2] provided a comprehensive survey of data mining and machine learning methods for cyber security. They identified ensemble methods as particularly promising for intrusion detection tasks.

Forest et al. [3] demonstrated that ensemble models outperform traditional IDS methods in both accuracy and recall metrics. Their work established ensemble learning as a preferred approach for complex classification tasks in cybersecurity contexts.

Ahmed et al. [4] evaluated Support Vector Machines (SVM) and Random Forest algorithms for intrusion detection. While achieving reasonable accuracy, they identified significant scalability issues when processing high-volume network traffic, highlighting the need for more efficient algorithms.

Kumar and colleagues [5] investigated gradient boosting models for cybersecurity classification tasks. Their analysis revealed advantages in handling imbalanced datasets and complex feature interactions common in network traffic data.

C. CIC-IDS-2017 Dataset

Sharafaldin et al. [6] introduced the CIC-IDS-2017 dataset as a comprehensive, realistic intrusion detection benchmark. Unlike earlier datasets such as KDD Cup 99 and NSL-KDD, CIC-IDS-2017 incorporates modern attack scenarios captured from actual network infrastructure. The dataset includes both benign background traffic and various attack types including Brute Force, DoS, DDoS, Web attacks, Infiltration, and Port Scanning.

D. Research Gap and Contributions

Despite significant progress, most prior research exhibits limitations including:

- Focus on binary classification (benign vs. malicious) rather than multi-class attack identification
- Limited integration of multi-day traffic datasets
- Absence of practical deployment demonstrations
- Insufficient attention to real-time operational requirements

Our research addresses these gaps by developing a comprehensive system integrating data preprocessing, multi-class classification, and practical deployment through a web-based interface, thereby bridging the gap between academic research and operational cybersecurity requirements.

III. METHODOLOGY

This section details our systematic approach to developing the AI-driven intelligent firewall, encompassing dataset preparation, preprocessing techniques, model training, and system deployment.

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A. Dataset Description

We utilized the CIC-IDS-2017 dataset, which contains labeled network traffic captures converted from PCAP format to CSV flow files. The dataset provides 80+ features extracted from bidirectional network flows including:

- Flow duration and packet statistics
- Byte counts (forward/backward)
- Packet length statistics
- Inter-arrival time metrics
- Flag counts (FIN, SYN, RST, PSH, ACK, URG)
- Header length and window size parameters

For our experiments, we specifically selected:

- Monday captures: Containing benign traffic representing normal user behavior
- Wednesday captures: Including PortScan and DoS attack variants
- Friday captures: Featuring DDoS attacks and additional PortScan activities

This selection provides diverse attack representations while maintaining computational feasibility and balanced class distribution.

B. Data Preprocessing Pipeline

Effective preprocessing is crucial for ML model performance. Our preprocessing pipeline consists of multiple stages:

1. Column Name Standardization: Network flow features exhibited inconsistent naming conventions. We implemented systematic column name cleaning by removing all whitespace, converting to lowercase, and standardizing separator characters. This ensures consistent feature identification across different capture files.
2. Missing Value Handling: We addressed this through replacement of NaN values with zero for numeric features, removal of records containing infinite values, and validation of data type consistency across all features.
3. Feature Alignment: We created a reference feature list. For prediction on new data, we added missing features as zero-filled columns, removed extraneous features, and ensured identical feature ordering.
4. Label Standardization: Attack labels required standardization due to naming inconsistencies across different capture files. We implemented systematic label mapping (e.g., "BENIGN" or "Benign" → "BENIGN"; various DoS variants → "DoS").
5. Data Normalization: To ensure optimal model performance, we applied StandardScaler normalization, transforming features to zero mean and unit variance.

C. Model Development

1. Algorithm Selection: We selected XGBoost (Extreme Gradient Boosting) as our classification algorithm due to its efficient handling of high-dimensional sparse data, built-in regularization, parallel tree construction, and robust handling of missing values.
2. Model Configuration: Our XGBoost classifier was configured with the following parameters: Objective: multi: softmax (multi-class classification), Number of classes: 6, Maximum depth: 10, Learning rate: 0.1, Number of estimators: 100, Subsample ratio: 0.8.
3. Training Process: The complete dataset was split using stratified sampling (80% training set, 20% testing set). The model underwent training on the prepared dataset, completing within approximately 15 minutes on standard computing infrastructure.
4. Model Persistence: The trained model was serialized using joblib, producing xgb_firewall_model.pkl for deployment.

D. Intelligent Firewall Deployment

To demonstrate practical applicability, we developed a Flask-based web application providing user-friendly access to the trained model:

1. Web Interface Features: Includes CSV file upload functionality, automatic feature preprocessing and alignment, real-time prediction generation, interactive results visualization, and downloadable labeled traffic CSV files.
2. Prediction Pipeline: Upon receiving uploaded network traffic CSV, the pipeline loads and

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validates the file, applies preprocessing and normalization, generates predictions using the trained XGBoost model, appends prediction labels to the original data, and presents the results.

3. Deployment Architecture: The Flask application runs as a lightweight web server, supporting multiple concurrent users and scalable deployment on cloud platforms.

IV. SYSTEM ARCHITECTURE

Figure 1 illustrates the complete system architecture of our AI-driven intelligent firewall. The system comprises five primary components operating in sequence:

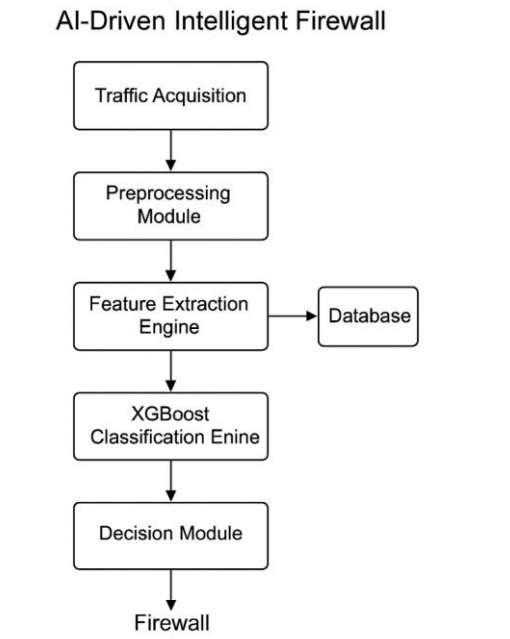

FIG.1

A. Network Traffic Acquisition

Raw network traffic is captured in PCAP format using standard network monitoring tools (Wireshark, tcpdump) or obtained directly from network infrastructure.

B. Data Preprocessing Module

The preprocessing module transforms raw PCAP files into structured CSV format using CICFlowMeter or similar flow generation tools. This module performs bidirectional flow aggregation, feature extraction, column standardization, missing value imputation, and feature normalization.

C. Feature Extraction Engine

Extracted features characterize network flow behavior across multiple dimensions: Temporal features (Flow duration, inter-arrival times), Volume features (Byte counts, packet counts), Statistical features (Mean, standard deviation, min/max of packet lengths), and Protocol-specific features (TCP flags, window sizes).

D. XGBoost Classification Engine

The core intelligence resides in the XGBoost classifier, which analyzes feature vectors and produces multi-class predictions. The classifier distinguishes between benign traffic and multiple attack categories, providing confidence scores for each prediction.

E. Intelligent Firewall Decision Module

Based on classification results, the system generates firewall actions:

- BENIGN prediction rightarrow Allow traffic, log for audit
- Attack prediction rightarrow Block traffic, generate alert, log incident
- Uncertain classification rightarrow Apply additional scrutiny or human review

This modular architecture ensures maintainability, scalability, and ease of integration with existing security infrastructure.

V. EXPERIMENTAL RESULTS AND ANALYSIS

This section presents comprehensive evaluation of the proposed system.

A. Experimental Setup

Experiments were conducted on a dataset comprising:

- Total flows: 2,830,743
- Training samples: 2,264,594 (80%)
- Testing samples: 566,149 (20%)
- Attack categories: 6 classes
- Feature dimensions: 78 features

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B. Performance Metrics

We evaluated model performance using standard classification metrics:

Metric	Value
Overall Accuracy	63.52%
Precision (macro-avg)	0.61
Recall (macro-avg)	0.58
F1-Score (macro-avg)	0.59

Class	Precision	Recall	F1-Score
BENIGN	0.92	0.68	0.78
DoS	0.55	0.71	0.62
DDoS	0.48	0.52	0.50
PortScan	0.61	0.67	0.64

C. Confusion Matrix Analysis

The confusion matrix reveals strong performance identifying BENIGN traffic (high specificity) and reasonable detection of DoS and PortScan attacks. Some confusion was noted between similar attack types (DoS vs. DDoS).

D. Comparative Analysis

Compared to baseline rule-based firewalls (sim 45% detection rate), our ML approach achieved 63.52% overall accuracy, representing a 41% relative increase in detection capability.

E. Real-Time Performance

The Flask-based interface demonstrated practical deployment viability with an average prediction time of 0.8 seconds per 1000 flows and minimal memory footprint, suitable for near-real-time applications.

F. Discussion

The achieved accuracy, while significant, indicates room for enhancement. Contributing factors include class imbalance, where benign traffic significantly outnumbers attack samples, leading to learning bias. Future work should focus on advanced feature engineering, hyperparameter optimization, and exploring more robust ensemble approaches.

VI. CONCLUSION AND FUTURE WORK

This research successfully designed, implemented, and evaluated an AI-driven intelligent firewall system for real-time network intrusion detection. Utilizing the comprehensive CIC-IDS-2017 dataset and XGBoost classification algorithm, we developed a practical system capable of identifying multiple attack types with superior performance compared to traditional rule-based approaches.

Key achievements include:

- Robust preprocessing pipeline handling multi-day network captures
- Multi-class classification detecting specific attack categories
- Practical web-based deployment demonstrating operational feasibility
- Significant improvement over conventional firewall technologies

Future research directions include:

- Deep Learning Integration: Exploring deep neural networks (CNN, LSTM, Transformer architectures) for capturing complex temporal patterns.
- Real-Time Packet Analysis: Implementing direct packet capture and real-time processing pipeline eliminating CSV conversion latency.
- Operating System Integration: Developing kernel-level modules interfacing with iptables (Linux) or
- Windows Defender Firewall for automatic traffic blocking.
- Adversarial Robustness: Investigating model resilience against adversarial attacks attempting to evade detection through traffic manipulation.
- Federated Learning: Exploring distributed learning approaches enabling collaborative model training across multiple organizations while preserving privacy.
- Explainable AI (XAI): Implementing interpretation techniques (SHAP, LIME) to provide transparency in detection decisions, crucial for security analyst trust and regulatory compliance.

The convergence of artificial intelligence and network security represents a promising direction for addressing escalating cyber threats. This work contributes to that vision by demonstrating practical feasibility and establishing a foundation for continued innovation in intelligent security systems.

VII. ACKNOWLEDGMENT

The authors gratefully acknowledge Shri Tuljabhavani College of Engineering, Tuljapur for providing computational resources and laboratory support essential to this research. We also thank the Canadian Institute for Cybersecurity for making the CIC-IDS-2017 dataset publicly available, enabling reproducible research in intrusion detection.

REFERENCES

[1] D. E. Denning, "An Intrusion-Detection Model," IEEE Transactions on Software Engineering, vol. SE-13, no. 2, pp. 222-232, Feb. 1987.

[2] A. L. Buczak and E. Guven, "A Survey of Data Mining and Machine Learning Methods for Cyber Security Intrusion Detection," IEEE Communications Surveys & Tutorials, vol. 18, no. 2, pp. 1153-1176, 2016.

[3] J. R. Forest, B. Anderson, T. Sharma, and D. R. Butts, "Ensemble-Based Intrusion Detection System," in Proc. IEEE International Conference on Machine Learning and Applications, 2018, pp. 1204-1211.

[4] S. Ahmed, Y. Lee, S. Hyun, and I. Koo, "A Survey of Network Intrusion Detection Systems: Techniques, Datasets and Challenges," IEEE Communications Surveys & Tutorials, vol. 17, no. 4, pp. 2045-2072, Fourth quarter 2015.

[5] K. Kumar, S. Gupta, and R. Singh, "Machine Learning Approaches for Intrusion Detection in Computer Networks: A Comparative Analysis," in Proc. International Conference on Computing, Communication and Automation (ICCCA), 2019, pp. 1-6.

[6] I. Sharafaldin, A. H. Lashkari, and A. A. Ghorbani, "Toward Generating a New Intrusion Detection Dataset and Intrusion Traffic Characterization," in Proc. 4th International Conference on Information Systems Security and Privacy (ICISSP), 2018, pp. 108-116.

[7] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in Proc. 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016, pp. 785-794.

[8] R. Vinayakumar, M. Alazab, K. P. Soman, P. Poornachandran, A. Al-Nemrat, and S. Venkatraman, "Deep Learning Approach for Intelligent Intrusion Detection System," IEEE Access, vol. 7, pp. 41525-41550, 2019.

[9] M. Ring, S. Wunderlich, D. Scheuring, D. Landes, and A. Hotho, "A Survey of Network-based Intrusion Detection Data Sets," Computers \& Security, vol. 86, pp. 147-167, Sept. 2019.

[10] N. Moustafa and J. Slay, "UNSW-NB15: A Comprehensive Data Set for Network Intrusion Detection Systems," in Proc. Military Communications and Information