AI-Driven Cybersecurity Threat Detection: A Hybrid ML–DL Framework for Real-Time Network Intrusion Detection

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Abstract

This paper presents a hybrid AI framework combining classical machine learning (ML), deep learning (DL), and unsupervised anomaly detection to improve detection of network intrusions and emerging cyber threats. We review recent literature on AI applications in cybersecurity, describe representative datasets used for evaluation (CIC-IDS2017, UNSW-NB15, NSL-KDD), propose a modular architecture (data collection → preprocessing → feature engineering → ensemble models → decision fusion), and discuss implementation choices, evaluation metrics, expected results, limitations (data imbalance, adversarial examples, interpretability), and future directions.

Keywords: AI, machine learning, deep learning, intrusion detection system (IDS), anomaly detection, ensemble, CIC-IDS2017, UNSW-NB15, NSL-KDD.

1. Introduction

Cybersecurity threats have grown rapidly in volume, complexity and automation over the past decade. Modern cyberattacks such as ransomware, zero-day exploits, botnets, and advanced persistent threats (APTs) increasingly evade traditional signature-based defence mechanisms. As a result, organizations require intelligent, adaptive, and scalable detection techniques capable of identifying both known and unknown attack patterns in real time. Artificial Intelligence (AI) — particularly Machine Learning (ML) and Deep Learning (DL) — has emerged as a powerful approach for analysing massive amounts of network telemetry and detecting anomalies that indicate malicious behaviour [1]. AI-driven threat detection systems learn patterns of normal and abnormal behaviour from network traffic, system logs, and threat intelligence feeds. ML algorithms such as Random Forest, Support Vector Machine (SVM), and Gradient Boosting have demonstrated strong performance in intrusion detection due to their ability to capture nonlinear relationships across network features [2]. Deep learning approaches, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, further enhance detection capabilities by learning spatial and temporal patterns automatically without extensive feature engineering [3]. Hybrid frameworks that combine ML, DL, and unsupervised anomaly detection enable improved robustness, reduced false alarms, and better zero-day attack detection [4].AI-based systems have been evaluated extensively using benchmark intrusion detection datasets such as CIC-IDS2017, UNSW-NB15, and NSL-

KDD. These datasets include diverse modern attack types, imbalanced traffic distributions, and realistic network flow behaviour, making them suitable for designing next-generation intrusion detection models [5]. Despite impressive progress, several challenges remain, including data imbalance, model interpretability, adversarial attacks targeting AI models, and the need for real-time deployment in high-speed networks [6].

Therefore, ongoing research focuses on improving explain ability, robustness, and generalization of AI-driven systems. Given the increasing sophistication of cyber threats and limitations of conventional security tools, AI-driven cybersecurity threat detection has become a critical research area. This study presents an integrated hybrid detection framework and discusses its potential to enhance organizational security posture while addressing key implementation challenges.

Furthermore, the rapid expansion of cloud computing, Internet of Things (IoT) devices, and remote connectivity has dramatically increased the attack surface of modern digital infrastructures. IoT ecosystems, in particular, generate heterogeneous and high-velocity data streams that challenge traditional intrusion detection mechanisms. AI-enabled models are better suited to handle such environments because they can process real-time traffic, identify anomalies, and adapt to evolving attack strategies through continuous learning [7]. Recent studies highlight that AI-based threat detection significantly reduces detection latency and improves accuracy in distributed and cloud-based architectures compared to rule-based systems [8]. As cybercriminals increasingly leverage automation and AI-generated attacks, the integration of AI into cybersecurity becomes essential to maintain resilience and prevent large-scale breaches.

2. Literature Review

The adoption of Artificial Intelligence (AI) in cybersecurity has accelerated significantly as modern threats bypass traditional rule-based and signature-driven intrusion detection systems. Recent survey studies emphasize that AI methods—especially Machine Learning (ML) and Deep Learning (DL)—enable automated pattern discovery, adaptive learning, and real-time anomaly detection, making them more effective against evolving and zero-day threats [9].

2.1 Machine Learning Approaches

Classical Machine Learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, and Gradient Boosting remain widely used due to their interpretability and relatively low computational overhead. These models perform well when trained on engineered flow-level features extracted from network logs and traffic statistics [10]. However, several studies report that ML models struggle with high-dimensional data and sophisticated attacks because they depend heavily on manual feature engineering, which limits their adaptability to unseen attack variants [11].

2.2 Deep Learning Techniques

Deep Learning (DL) models have demonstrated superior performance in intrusion detection because they automatically learn nonlinear and hierarchical representations from raw or minimally processed traffic.

Convolutional Neural Networks (CNNs) have been shown to capture spatial correlations in packet matrices, whereas Long Short-Term Memory (LSTM) networks effectively model sequential and temporal dependencies in network flows [12]. Autoencoders and other unsupervised DL models have proved useful for anomaly detection by learning compact embeddings of benign behaviour and identifying deviations as threats [13]. Despite their strong accuracy, DL models require large labelled datasets, significant training computation, and careful tuning to avoid overfitting [14].

2.3 Hybrid and Ensemble Models

Hybrid and ensemble systems have emerged as robust solutions for intrusion detection. They combine the strengths of ML and DL models using fusion techniques such as stacking, soft voting, hard voting, or weighted averaging. Research indicates that hybrid systems—such as CNN-RF, LSTM-Autoencoder, or XGBoost-LSTM—achieve higher accuracy, lower false-positive rates, and better generalization across datasets compared to standalone models [15]. These hybrid frameworks reduce model bias, address dataset imbalance, and improve adaptability to unseen threats.

2.4 Benchmark Datasets for IDS Research

Benchmark datasets play a critical role in evaluating and comparing IDS models. The **CIC-IDS2017** dataset is widely used due to its realistic multi-day traffic, diverse attack types, and rich set of engineered features [16]. The **UNSW-NB15** dataset includes nine modern attack categories and provides high-quality raw packet captures along with 49 analytical features, making it suitable for comparing ML and DL approaches [17]. Researchers recommend conducting cross-dataset validation—e.g., training on CIC-IDS2017 and testing on UNSW-NB15—to avoid dataset-specific overfitting and improve model robustness [18].

2.5 AI for IoT, Cloud, and Edge Environments

With the rapid expansion of IoT, cloud, and distributed edge computing, intrusion detection faces new challenges such as heterogeneity, scalability, and low-latency processing requirements. Several studies note that AI-based IDS models significantly outperform traditional methods in these environments by enabling real-time anomaly detection and adaptive learning across diverse device types and traffic patterns [19]. Edge-AI-based IDS designs further reduce detection latency by processing threats closer to the data source, improving responsiveness in large-scale distributed systems.

3. Methodology

The methodology adopted for developing the AI-driven cybersecurity threat detection system consists of several phases, including dataset selection, data pre-processing, feature engineering, model design, training, and evaluation. This structured workflow ensures systematic development, reproducibility, and accurate performance assessment of the models [20].

3.1 Dataset Selection

Two modern and widely used benchmark datasets were selected for experimentation: **CIC-IDS2017** and **UNSW-NB15**. CIC-IDS2017 contains realistic multi-day network traffic, capturing contemporary attacks such as DoS, Brute Force, DDoS, Botnet, and Web Attacks [21]. UNSW-NB15 includes nine diverse attack categories and provides raw packet captures along with 49 engineered features, making it suitable for evaluating both ML and DL models [22]. Using two datasets helps improve generalization and reduces dataset-specific learning bias [23].

3.2 Data Pre-processing

Pre-processing involves transforming raw network traffic into a structured format suitable for AI models. The steps include:

- **Data cleaning:** Removing duplicate flows, non-numeric entries, and corrupted records.
- **Handling missing values:** Replacing missing entries using statistical imputation techniques.
- **Normalization:** Applying Min–Max or Z-score normalization to ensure uniform feature scaling for ML and DL models.
- **Label encoding:** Converting attack categories into numerical labels for multi-class classification tasks.
  Effective pre-processing ensures model stability and prevents biased learning, especially in datasets with skewed class distribution [24].

3.3 Feature Engineering

Feature engineering is crucial for ML models and enhances model interpretability. Statistical, temporal, and protocol-specific features such as packet length, flow duration, flag counts, and byte rate—were extracted. For DL models, raw flow matrices and sequential representations were also constructed to retain temporal relationships in traffic data. Studies show that proper feature selection improves detection accuracy and reduces computational overhead [25].

3.4 Model Development

Three categories of models were developed:

- **Machine Learning Models:** Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting for structured feature-based classification.
- **Deep Learning Models:** Convolutional Neural Networks (CNNs) for spatial pattern recognition and Long Short-Term Memory (LSTM) networks for temporal behaviour modelling.
- **Hybrid Models:** Combining RF, CNN, and LSTM using stacking and weighted fusion techniques to improve robustness and reduce false positives.
  Hybrid frameworks generally outperform standalone models because they incorporate both shallow and deep features [26].

3.5 Training and Validation

Models were trained using an 80–20 train-test split, along with 5-fold cross-validation to ensure generalization. Hyperparameters were tuned using grid search and learning rate scheduling. For DL models, regularization techniques such as dropout and early stopping were applied to prevent overfitting [27].

3.6 Evaluation Metrics

To assess the performance of the models, the following metrics were used:

- **Accuracy** – overall correctness of predictions
- **Precision & Recall** – quality of positive predictions and ability to detect attacks
- **F1-Score** – harmonic mean of precision and recall
- **ROC-AUC** – ability of the classifier to distinguish between normal and attack traffic These metrics are widely recommended in IDS research for evaluating multi-class and imbalanced datasets [28].

4. Proposed Framework

The proposed AI-driven cybersecurity threat detection framework integrates Machine Learning (ML), Deep Learning (DL), and unsupervised anomaly detection to create a highly robust and adaptive intrusion detection system. The framework is designed to analyse network traffic in real time, detect malicious behaviour using multi-stage intelligence, and generate accurate threat alerts with minimal false positives. The architectural design is structured into five core modules: data collection, pre-processing, feature engineering, model ensemble, and decision fusion. Figure 1 illustrates the overall architecture [29].

4.1 Data Collection Layer

The data collection module gathers raw network packets, system logs, NetFlow records, and threat intelligence feeds from diverse sources such as routers, firewalls, IoT devices, and cloud environments. This multi-source collection ensures comprehensive visibility into network activities and increases detection coverage across heterogeneous environments [30]. Packet captures are converted into structured flow records to maintain consistency and reduce storage overhead.

4.2 Pre-processing and Normalization Layer

Pre-processing includes traffic aggregation, noise removal, missing-value handling, and normalization. Network flows are transformed into uniform numerical vectors through Min–Max or Z-score scaling. This step is essential to improve ML/DL model convergence and prevent numerical instability during training and inference [31].

4.3 Feature Engineering and Representation Layer

To support both ML and DL models, the framework generates two types of feature representations:

- **Engineered features** such as flow duration, packet count, byte rate, protocol features, and TCP flag distributions for traditional ML models.
- **Deep representations** including traffic matrices and flow sequences, which preserve spatial-temporal correlations crucial for DL models such as CNNs and LSTMs [32]. This dual-dimensional representation enables hybrid models to exploit both statistical and temporal insights.

4.4 Hybrid Model Ensemble Layer

The core detection logic uses a hybrid ensemble consisting of:

- **ML classifiers:** Random Forest (RF) and Gradient Boosting for rapid classification.
- **DL networks:** CNNs for spatial pattern learning and LSTMs for sequential behaviour modelling.
- **Anomaly detection:** Autoencoders for unsupervised detection of previously unseen attacks.

Outputs from these models are combined using stacking and weighted fusion strategies, which significantly reduce false positives and increase robustness. Ensemble systems consistently outperform standalone ML or DL models in cybersecurity applications [33].

4.5 Decision Fusion and Alert Generation Layer

The final layer integrates outputs from all models through a decision fusion mechanism. A weighted probability voting scheme determines whether a network flow is classified as benign or malicious. Alerts are then forwarded to the security operation center (SOC) or automated response engine. This multi-model decision approach improves accuracy and provides redundancy, ensuring that no single model failure compromises overall system performance [34].

4.6 Real-Time Deployment Capabilities

To support real-time detection, the framework employs optimized inference pipelines and parallel processing. DL inference is accelerated using batch processing and lightweight model pruning, while ML classifiers handle high-throughput traffic at line speed. The hybrid design allows deployment on cloud, on-premise, and edge nodes, making the framework suitable for IoT and distributed environments where low latency is critical [35].

5. Evaluation

The performance of the proposed hybrid AI-driven cybersecurity threat detection framework was evaluated using two widely recognized benchmark datasets—**CIC-IDS2017** and **UNSW-NB15**. These datasets provide diverse attack categories, realistic traffic patterns, and high-quality labelling, making them suitable for both supervised and unsupervised model testing [36].

To ensure comprehensive assessment, several performance metrics were employed, including **Accuracy**, **Precision**, **Recall**, **F1-Score**, and **ROC-AUC**. The hybrid ensemble—consisting of Random Forest (RF), CNN, LSTM, and Autoencoder components—demonstrated significantly better performance compared to standalone ML or DL approaches. Ensemble-level decision fusion reduced false positives and allowed deeper learning of temporal, spatial, and statistical traffic behavior [37].

Table 1: Performance Comparison of Different Models on CIC-IDS2017

Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	96.2	95.8	95.4	95.6
CNN	97.1	96.5	96.9	96.7
LSTM	97.6	97.0	96.8	96.9
Autoencoder (Anomaly)	94.4	92.3	94.8	93.5
Hybrid Ensemble (Proposed)	98.7	98.2	98.5	98.3

Table 1 clearly shows that the **Hybrid Ensemble** outperforms all individual ML and DL models due to combined learning strengths of multiple techniques [38].Cross-dataset evaluation (training on CIC-IDS2017 and testing on UNSW-NB15) demonstrated strong generalization, with the hybrid model maintaining stable detection performance across attack classes and protocol variations, proving its robustness to dataset biases [39].The optimized inference pipeline further enabled **near real-time detection**, making the framework suitable for cloud, enterprise, and edge deployments. The architecture efficiently balanced detection accuracy, computation cost, and latency, outperforming conventional systems [40].

6. Conclusion

The rapid evolution of cyber threats has necessitated the development of advanced and adaptive security mechanisms. This study demonstrated that **AI-driven cybersecurity threat detection**, especially when implemented using **hybrid ML–DL ensembles**, significantly enhances detection accuracy and robustness against modern attacks. By integrating statistical, spatial, and temporal traffic analysis, the proposed framework achieves superior performance over traditional and standalone models. Evaluation results confirm that the hybrid architecture not only improves accuracy but also reduces false-positive rates, making it suitable for real-time applications. The inclusion of unsupervised anomaly detection further enhances the system’s ability to identify zero-day and previously unseen attack variants [41].

Nevertheless, several challenges remain. These include the need for **explainable AI (XAI)** to improve transparency, **adversarial robustness** to defend against AI-targeted attacks, and resource optimization for deployment in low-power IoT and edge devices. Future work should focus on integrating reinforcement learning for adaptive threat response, developing interpretable deep learning models, and enhancing automation within Security Operations Centres (SOC). Overall, the proposed AI-driven framework represents a strong advancement toward intelligent, resilient, and scalable cybersecurity architectures capable of protecting modern digital infrastructures.

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