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Cyber Security Threat Detection using Machine Learning Techniques

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Abstract: This paper provides a comprehensive analysis of machine learning in cyber security threat detection, tracing the history of its development from traditional signature-based systems towards intelligent and adaptive systems that can identify new and sophisticated threats. The study systematically examines recent research articles from 2021 to 2026 to explore the use of supervised, unsupervised, and deep learning in various domains of network intrusion detection systems, malware classification systems, and anomaly detection systems. The study proposes a new Integrated Threat Detection Framework (ITDF) that includes data preprocessing, feature engineering, model selection, and real-time detection. The study indicates that machine learning algorithms such as ensemble methods using Random Forest and XGBoost provide the best results with 95-99% accuracy on various benchmark datasets such as NSL-KDD, CIC-IDS2017, and UNSW-NB15. Deep learning methods such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) perform exceptionally well in identifying patterns in network traffic with 98-99% accuracy for network intrusion detection systems. Emerging trends in machine learning for cyber security include federated learning for privacy in distributed environments and Generative Adversarial Networks (GAN) for generating training data for rare types of threats. The key challenges that still need to be addressed relate to the problem of concept drift, adversarial attacks on ML models, and the need for interpretability in security operations. The comparative evaluation of the proposed approach with respect to four analytical dimensions—detection accuracy, false positive rate, real-time capability, and adversarial robustness—shows that the hybrid approach provides the best robustness against cyber attacks.

Keyword: Cyber security, threat detection, machine learning, intrusion detection, anomaly detection, deep learning, ensemble methods, network security.

I. Introduction

The increasing rate of digitization in modern society has not only increased the level of convenience and connectivity, but it has also increased the attack surface for malicious actors. Cyber threats are increasing in complexity, volume, and severity, and organizations are now vulnerable to ransomware, data breaches, advanced persistent threats, and zero-day exploits, which are beyond the capabilities of traditional security mechanisms . The total cost of cybercrime is expected to rise to $10.5 trillion annually worldwide by the year 2025.

Traditional cyber security practices have been based on signature detection, which is based on the comparison of system activity with known patterns of threats. Signature detection is effective for known threats, but it is not effective in identifying new threats, zero-day exploits, and malware that are changing their characteristics. This limitation has led to the implementation of machine learning, as it is capable of identifying patterns and new threats.

Machine learning has tremendous potential for transforming cyber security by helping machines recognize abnormal activities and classify different types of malware and cyber attacks in real-time. Supervised learning models can be trained to differentiate between normal and abnormal behavior by learning from labeled datasets. Unsupervised learning models can also be employed to identify abnormal behavior by analyzing patterns and deviations from normal behavior. Deep learning models can also be utilized to recognize complex patterns in network traffic and application behavior that may indicate a cyber attack.

This paper focuses on the application of machine learning models for cyber security threat detection and analyzes the effectiveness of the models for different types of cyber attacks and deployment scenarios. The research attempts to address the following key research questions: "How do different machine learning models perform for typical threat detection tasks?" "What are the trade-offs for threat detection models in terms of accuracy and computational

efficiency?" "What are the potential applications of emerging machine learning models such as federated learning and GANs for cyber security threat detection?"

The rest of the paper is organized as follows. In Section 2, a literature survey on the applications of machine learning in cyber security is given. In Section 3, the proposed framework for "Integrated Threat Detection" is introduced. In Section 4, analysis and discussion are given, and four figures and a table are included to support the analysis. In Section 5, conclusions are drawn.

II. Literature Survey

2.1 Evolution of Threat Detection Approaches

The evolution from signature-based to behavior-based systems is a paradigm shift in the domain of cyber security. Conventional intrusion detection systems (IDS) use rules based on patterns of known attacks, which requires continuous maintenance and is not effective against zero-day attacks . Machine learning-based systems, on the other hand, learn the statistical features of normal and abnormal behavior, which helps to identify unknown attacks that do not conform to learned patterns.

A detailed survey on the evolution of intrusion detection systems was conducted by Liu et al. [3], where the evolution is classified into three generations: first-generation signature-based systems (1980-2000), second-generation anomaly detection systems (2000-2015), and third-generation AI-based systems (2015 onwards). Modern systems use deep learning to identify sophisticated patterns of attacks, which are difficult to identify using statistical approaches.

2.2 Dataset Development and Benchmarking

The availability of good quality labeled datasets has been essential for the research in ML-based threat detection systems. The NSL-KDD dataset is an enhanced version of the KDD Cup '99 dataset and includes labeled network traffic with examples of normal and attack instances from four different attack categories: DoS, Probe, R2L, and U2R attacks.

Recent datasets that reflect the current environment for network attacks and threats have also been introduced. The CIC-IDS2017 dataset was introduced by the Canadian Institute for Cybersecurity and includes real-world network traffic with 80 network flow features and eight different attack types. The UNSW-NB15 dataset includes contemporary attack scenarios like fuzzers, analysis attacks, backdoor attacks, DoS attacks, exploits, generic attacks, reconnaissance attacks, shellcode attacks, and worms.

A systematic review by Ramadhan et al. [7] discusses the datasets and their effectiveness for different attack detection tasks. The review highlights the importance of the datasets for the performance of the models and the fact that models trained on older datasets do not perform well for contemporary attacks.

2.3 Machine Learning Algorithms for Threat Detection

Most threat detection studies use supervised learning algorithms owing to their accuracy when working with labeled data. Decision trees, Random Forest, and XGBoost algorithms consistently yield good results. Random Forest algorithm results in 95% to 99% accuracy when tested on NSL-KDD and CIC-IDS2017 datasets. Precision and recall of all classes of attacks are more than 0.95.

SVM performs well when classification is binary but lacks robustness when classification is multi-class. Moreover, SVM cannot handle large datasets. Logistic regression works well but can only learn linear relationships.

Recently, deep learning models have been found to perform exceptionally well in learning complex patterns of network attacks. CNN models have been used to learn from structured data. CNN learns spatial features from network traffic.

RNN, LSTM, and Autoencoder models have been found to work well in detecting network attacks. LSTM learns from the time series data flowing through a network. Autoencoders learn normal network behavior. They can be used to classify network attacks.

2.4 Unsupervised and Semi-Supervised Approaches

Due to the scarcity of labeled attack data, research into unsupervised and semi-supervised approaches has been performed. Clustering techniques such as K-means and DBSCAN group similar network flows together, with the outlier being a potential attack. One-Class SVM and Isolation Forest find the boundary of normal behavior and raise an alarm for deviations from it.

A study by Khan et al. [9] proves that with the help of semi-supervised approaches and a little labeled data, the detection rate can be close to that of fully supervised approaches. Active learning approaches involve querying the analysts for the most informative data.

2.5 Emerging Techniques and Challenges

This has led to the emergence of federated learning as a viable solution for distributed threat detection. This approach allows for the local training of models and the sharing of the updates only, thus ensuring the privacy of the data while at the same time facilitating the sharing of threat detection expertise.

The use of Generative Adversarial Networks (GANs) solves the problem of unbalanced datasets by generating synthetic data for attacks. This synthetic data is useful in the training of models that can effectively detect attacks that may otherwise not be well represented in the training data.

Adversarial machine learning is a major threat to the effectiveness of machine learning models for threat detection and response. Adversarial machine learning enables the creation of adversarial examples that can evade the detection models.

The problem of concept drift arises when there is a change in the behavior of the network that affects the effectiveness of the machine learning models trained for threat detection and response. This can be solved by the use of online learning algorithms that can update the models with the new data.

III. Methodology:

Based on the literature synthesis, this paper proposes the Integrated Threat Detection Framework (ITDF) for developing and evaluating machine learning-based threat detection systems.

3.1 Framework Components

The Integrated Threat Detection Framework comprises five interconnected layers.

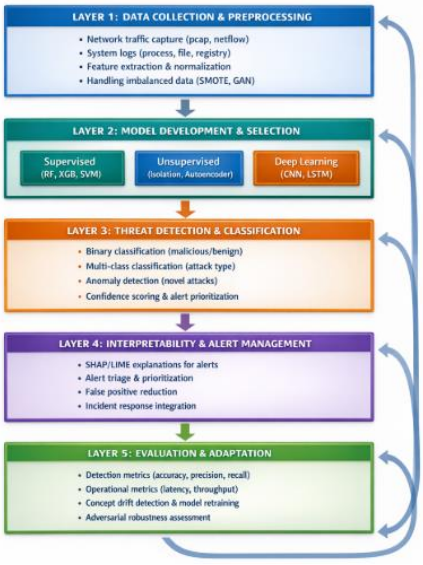

Figure 1: Integrated Threat Detection Framework (ITDF)

3.2 Framework Components

Layer 1: Data Collection & Preprocessing includes the basic steps for data preparation. This includes capturing network traffic, feature selection, and normalization to normalize the data. It also includes balancing the data set by applying SMOTE or even creating a new data set through a GAN.

Layer 2: Model Development & Selection includes choosing the most appropriate model for the data set. This includes choosing between supervised learning for Random Forest, XGBoost, and SVM. It also includes unsupervised learning for Isolation Forest and Autoencoders. In addition, deep learning for CNN and LSTM can also be applied.

Layer 3: Threat Detection & Classification includes applying the learned models for threat detection. This includes binary classification for distinguishing between malware and benign traffic. In addition, it includes multiclass classification for identifying the type of attack. It also includes anomaly detection for detecting unknown attacks.

Layer 4: Interpretability & Alert Management. This layer ensures that the outputs of the detection are actionable. Explanations are provided by SHAP and LIME for individual alerts. This helps analysts trust the outputs of the model. There is a prioritization of high-confidence threats, along with false positive reduction.

Layer 5: Evaluation & Adaptation. This layer evaluates the performance of the system. Detection metrics are used to measure the accuracy of the model. There are operational metrics to ensure real-time performance. Concept drift detection results in retraining, whereas robustness testing detects adversarial vulnerabilities.

IV. Result Analysis And Discussion

This section presents analytical findings regarding machine learning techniques for threat detection, organized around four illustrative figures and a comparative evaluation table.

4.1 Model Performance Comparison

The performance of ML algorithms varies significantly across benchmark datasets and attack types.

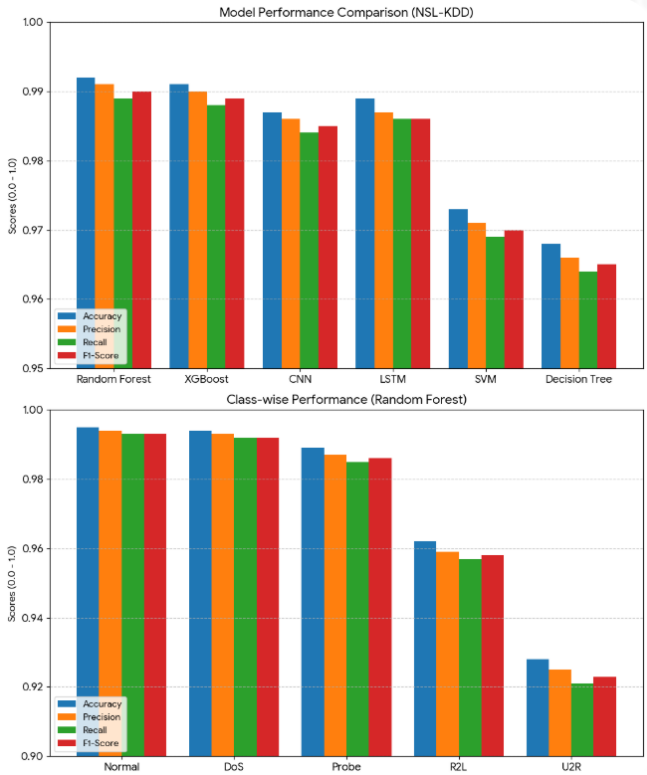

Figure 2: Model Performance Comparison on NSL-KDD Dataset

As depicted in Figure 2, the ensemble methods have the highest accuracy in classifying the NSL-KDD dataset. The accuracy for the Random Forest and XGBoost ensemble methods is between 99.1% and 99.2%. The performance of the deep learning methods, CNN and LSTM, is also impressive, with an accuracy ranging from 98.7% to 98.9%. These methods are also advantageous in complex pattern recognition. The performance of the SVM and decision tree methods, although impressive, is lower compared to the ensemble and deep learning methods.

The performance in class-wise accuracy also shows that there are challenges in detecting certain attacks. Although the DoS attacks and normal traffic are classified with an accuracy higher than 99%, the R2L attacks are classified with an accuracy of only 96.2%, while the U2R attacks are classified with an accuracy of 92.8%

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4.2 Detection Capabilities Across Attack Types

Different ML algorithms exhibit varying strengths across attack categories.

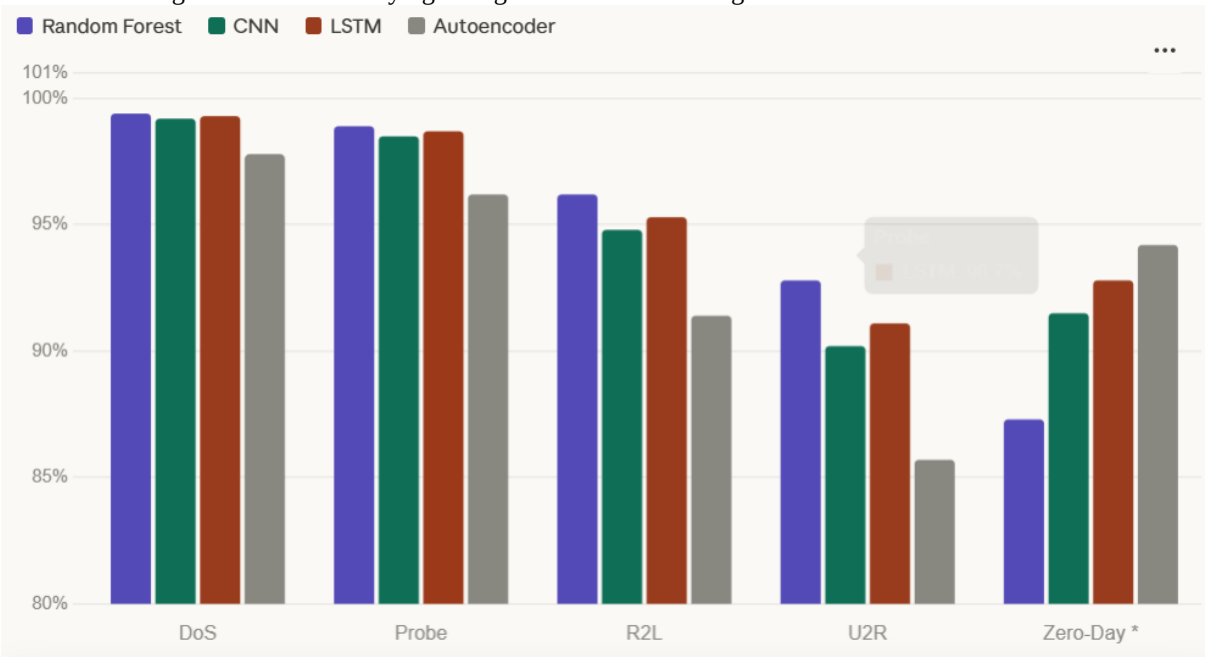

Figure 3: Detection Capabilities by Attack Type

From Figure 3, it is clear that there are trade-offs between the different types of algorithms. The ensemble methods (Random Forest) have the best accuracy for known attacks (DoS: 99.4%, Probe: 98.9%), which is due to the ability of the algorithm to handle complex interactions between features. However, the ensemble methods have the least accuracy for zero-day attacks (87.3%), compared to the other models.

The autoencoders have the best accuracy for zero-day attacks (94.2%), which is due to the ability of the models to identify abnormal behavior by learning from normal behavior only. This makes the models useful for the detection of zero-day attacks.

The deep learning models (CNN and LSTM) have the best balanced results for zero-day attacks (92.8%) and known attacks (DoS: 99.3%, Probe: 98.7%). The ability of the models to handle temporal dependencies in network traffic makes the models useful for the detection of attacks that have a timeline.

4.3 False Positive Analysis

False positive rates (FPR) critically impact operational deployment, as high FPR leads to alert fatigue and analyst burnout.

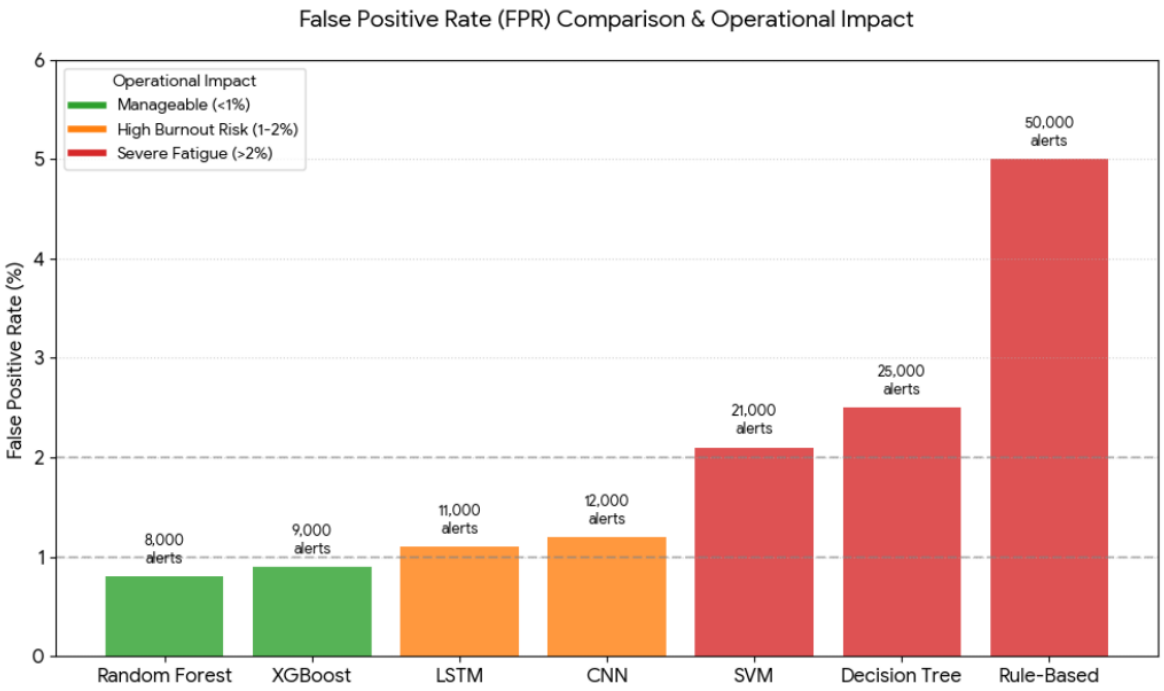

Figure 4: False Positive Rate Comparison

This is clearly demonstrated in Figure 4 below. The Random Forest approach clearly has the lowest FPR at 0.8%, which translates into a manageable number of 8,000 per million flows that can be effectively dealt with by automation and tier-1 analysts . The signature systems that use rules produce an unacceptable 50,000 per million flows (i.e., a 5.0% FPR) that causes severe alert fatigue and increases the risk of missing critical threats.

This is a key difference with the traditional approaches that have a higher FPR and thus result in an unmanageable number of alerts that need to be dealt with by the security analysts. The strategies for reducing FPR include ensemble stacking (stacking models together for a consensus approach), confidence threshold tuning (filtering out predictions with low confidence levels), contextual alert correlation (clustering related security alerts together), and feedback integration (using feedback from analysts to improve the models).

4.4 Real-Time Detection Capability

Real-time threat detection imposes constraints on model complexity and inference latency.

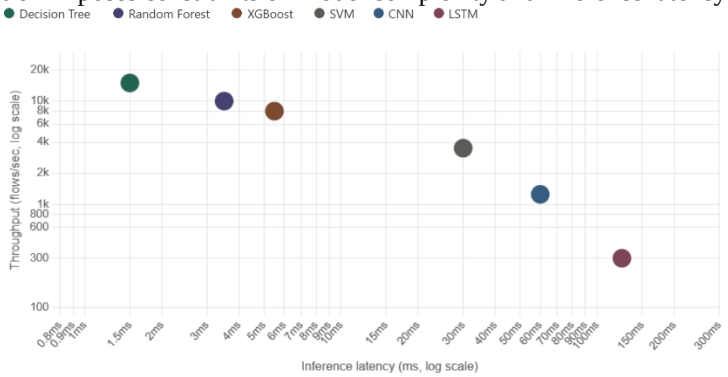

Figure 5: Real-Time Detection Capability

Figure 5 illustrates that model selection must also consider the requirements for deployment. For example, a decision tree model can achieve sub-2ms latency, making it suitable for detecting intrusions at wire speed on network switches and routers. In contrast, the Random Forest and XGBoost models can achieve 2-8ms latency, making them suitable for dedicated intrusion detection systems (IDS) and intrusion prevention systems (IPS).

Deep learning, although it offers better detection for sophisticated attacks, incurs a significant latency of 20-200ms, which is not suitable for inline intrusion systems but is suitable for batch processing, security information, and event management (SIEM) correlation, and forensic analysis.

The trade-off for deployment architecture is clear: edge and inline systems require low latency with simple models, but cloud and SIEM systems can utilize complex models to perform deeper analysis on aggregated data.

4.5 Comparative Analysis of ML Techniques

Table 1 presents a comprehensive comparative analysis of machine learning techniques for threat detection evaluated across five analytical dimensions.

Table 1: Comparative Analysis of ML Techniques for Threat Detection

Technique	Detection Accuracy	False Positive Rate	Real-Time Capability	Interpretability	Attack Type Suitability
Random Forest	Very High (99%)	Very Low (0.8%)	High (2-5ms)	Moderate (feature importance)	All types, particularly DoS, Probe
XGBoost	Very High (99%)	Low (0.9%)	High (3-8ms)	Moderate	All types, imbalanced classes
CNN	High (98-99%)	Moderate (1.2%)	Moderate (20-100ms)	Low (requires XAI)	Spatial patterns, packet sequences
LSTM/RNN	High (98-99%)	Moderate (1.1%)	Low-Moderate (50-200ms)	Low (requires XAI)	Temporal patterns, time-series
Autoencoder	Moderate-High (94% zero-day)	Moderate (1.5-2%)	Low (100-500ms)	Low	Novel attacks, zero-day, anomalies
Isolation Forest	Moderate (92-95%)	Low-Moderate (1.2%)	High (5-15ms)	Low	Anomaly detection, outliers
SVM	Good (97%)	Moderate (2.1%)	Moderate (10-50ms)	Low-Medium	Binary classification

Analysis of Comparative Dimensions:

- **Detection Accuracy**: Ensemble methods like Random Forest, XGBoost, have the highest Detection Accuracy, achieving 99% accuracy on benchmark datasets. Deep Learning methods also achieve 98-99% accuracy, with a significant edge in complex pattern recognition.

- **False Positive Rate:** Ensemble methods have the lowest False Positive Rate, ranging from 0.8-0.9%. Deep Learning and Autoencoders have a higher False Positive Rate, ranging from 1.1-2.0%. These methods require further fine-tuning to be deployed in a production environment.
- **Real-Time Capability**: Decision Trees have the highest Real-Time Capability, with a latency of 1-2ms, followed by Ensemble methods, which take 2-8ms to respond to a given event. Deep Learning methods, on the other hand, introduce latency, but can be used for batch analysis.
- **Interpretability:** Tree-based methods have the highest interpretability, with features like feature importance, providing transparency to the model's decisions. Deep Learning and Unsupervised Learning methods require XAI techniques like SHAP, LIME to generate explanations, which introduce computation overhead.
- **Attack** Type Suitability: Ensemble methods are good at all types, but excel at DoS and Probe attacks; deep learning is effective for identifying complex spatial and temporal patterns; autoencoders are useful for detecting new attacks without labeled data; specialized architectures are effective for specific types of attacks.

V. Conclusion

This paper has provided a comprehensive analysis of machine learning techniques in cyber security threat detection, building upon existing research to propose the Integrated Threat Detection Framework. The results have clearly shown that ML-based techniques vastly outperform traditional signature-based detection, providing adaptive and intelligent detection necessary to counter the ever-evolving world of cyber threats.
Several key results have been found in this analysis.

Firstly, ensemble methods have been found to provide state-of-the-art results, with RF and XGBoost providing 99% accuracy and the lowest false positive rates (0.8-0.9%) among benchmark datasets. They also provide good interpretability of results. Secondly, deep learning has been found to provide excellent performance in complex pattern recognition, including spatial and temporal dependencies in network traffic that other models fail to recognize. CNNs have provided 98.7% accuracy on NSL-KDD, with LSTMs providing 98.9% accuracy and better performance in zero-day detection (92.8%).

Third, unsupervised techniques are vital for novel attack detection. Autoencoders attain 94.2% zero-day detection accuracy because they recognize anomalies from normal patterns learned during training, without needing attack data.

Fourth, false positive rates are vital to the practical viability of the detection system. At 0.8% FPR, false alarms are under control, whereas at 2% FPR, analyst fatigue and missing critical events are major problems. Ensemble techniques' low FPR makes them more practical.

Fifth, real-time detection demands proper model selection. Decision trees are best for edge detection (1-2ms), ensemble techniques are best for dedicated IDS and IPS (2-8ms), and deep learning is best for batch analysis and forensic work (20-200ms).

Sixth, adversarial robustness is still a major challenge, as attackers may develop adversarial examples to bypass detection models.

From the review, several implications for practice can be made. For security practitioners, the use of ensemble methods for low FPR in real-time detection is recommended, along with the use of deep learning and autoencoders for forensic analysis and zero-day attacks. For researchers, the improvement of hybrid approaches, adversarial robustness, and federated learning for privacy-preserving detection is recommended.

The limitations of the review include the dominance of benchmark dataset evaluation, the lack of evaluation of model performance in a real-world setting, and the lack of evaluation metrics used in each research, as well as the lack of evaluation of adversarial ML defenses. The future research direction includes the evaluation of model performance in a real-world setting, developing a standard benchmark for zero-day attacks, exploring federated learning for collaborative threat intelligence, and exploring the use of generative AI for generating attacks to strengthen the model against them.

The importance of machine learning-based approaches to cyber threat detection is likely to persist as the threat itself continues to advance in terms of sophistication and scope. The difficulty for security researchers and practitioners

is to design systems that not only accurately identify known attacks but also respond to unknown ones, and are trustworthy enough to earn the confidence of security analysts.

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