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AI-Based Cyber Security Using Machine Learning For Intelligent Threat Detection

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Author Note

"This paper presents an AI-based cyber security framework using machine learning for intelligent detection of known and unknown cyber threats in real time."

Abstract

The increasing sophistication and volume of cyber-attacks pose significant challenges to traditional signature-based security mechanisms. To address these limitations, this paper presents an AI-based cyber security approach that utilizes machine learning techniques for intelligent threat detection. The proposed framework analyzes network traffic and system behavior to identify both known and unknown cyber threats through anomaly and pattern recognition. Supervised and unsupervised learning models are employed to enhance detection accuracy while minimizing false positive rates. Relevant features are extracted from network packets and system logs to train the models effectively. Experimental evaluation conducted on benchmark intrusion detection datasets demonstrates that the proposed system achieves improved performance in terms of detection accuracy, precision, and recall when compared to conventional intrusion detection systems. The results indicate that machine learning–driven security solutions can provide adaptive and scalable defense mechanisms capable of responding to evolving cyber threats in real time. This study emphasizes the potential of integrating artificial intelligence into cyber security infrastructures to develop proactive and resilient threat detection systems.

- **Keywords*:***

Cyber security , Machine Learning, Artificial Intelligence, Intrusion Detection System, Intelligent Threat Detection, Anomaly Detection, Network Security.

AI-Based Cyber Security Using Machine Learning For Intelligent Threat Detection

The rapid evolution of networked systems and cloud-based services has intensified the frequency and complexity of cyber-attacks, including advanced persistent threats, zero-day exploits, and distributed denial-of-service attacks. Traditional signature-based intrusion detection and prevention systems are limited by their dependence on predefined rules and known attack patterns, making them ineffective against emerging and previously unseen threats. Additionally, the high volume and velocity of network traffic pose scalability challenges for conventional security solutions. Artificial intelligence (AI) and machine learning (ML) techniques have gained significant attention for addressing these challenges by enabling automated, data-driven threat detection. Machine learning models can analyse high-dimensional network traffic and system-level features to identify malicious behaviour through classification and anomaly detection. Supervised, unsupervised, and hybrid learning approaches have been successfully applied to improve detection accuracy while reducing false positives. This paper presents an AI-based cyber security framework that leverages machine learning techniques for intelligent threat detection, aiming to enhance adaptability, scalability, and real-time security in modern cyber environments.

○ LITERATURE REVIEW

The increasing complexity of cyber threats has motivated extensive research on the application of machine learning techniques for intrusion detection and cyber security. Traditional signature-based intrusion detection systems rely on predefined attack patterns and are ineffective against zero-day and polymorphic attacks. As a result, researchers have explored data-driven approaches to enhance threat detection capabilities.

Several studies have applied supervised learning algorithms such as Support Vector Machines (SVM), Random Forests, Decision Trees, and k-Nearest Neighbors for detecting malicious activities in network traffic These methods have demonstrated high accuracy in classifying known attacks but require labeled datasets and often suffer from poor generalization to unseen threats. To address these limitations, unsupervised learning techniques, including clustering algorithms and anomaly detection models, have been proposed to identify deviations from normal behavior without prior attack knowledge.

Recent research has focused on deep learning approaches, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, to automatically extract complex features from high-dimensional network data .These models have shown improved performance in detecting advanced and stealthy attacks. Hybrid approaches combining supervised and unsupervised learning have also been introduced to reduce false positive rates and improve adaptability. Despite these advancements, challenges related to data imbalance, computational overhead, and real-time deployment remain open issues, highlighting the need for more efficient and interpretable AI-based cyber security solutions.

○ PROBLEM STATEMENT

Modern cyber environments generate large volumes of heterogeneous network and system data, making real-time threat detection increasingly complex. Traditional signature-based security systems rely on predefined rules and known attack patterns, limiting their effectiveness against emerging, zero-day, and evolving cyber threats. Existing machine learning–based intrusion detection approaches often suffer from high false positive rates, poor generalization to unseen attacks, and scalability challenges when deployed in dynamic network conditions. Additionally, issues such as data imbalance, feature redundancy, and computational overhead further reduce detection efficiency. Therefore, there is a critical need for an intelligent, adaptive, and scalable cyber security framework that leverages machine learning techniques to accurately detect both known and unknown threats while ensuring real-time performance and reduced false alarms.

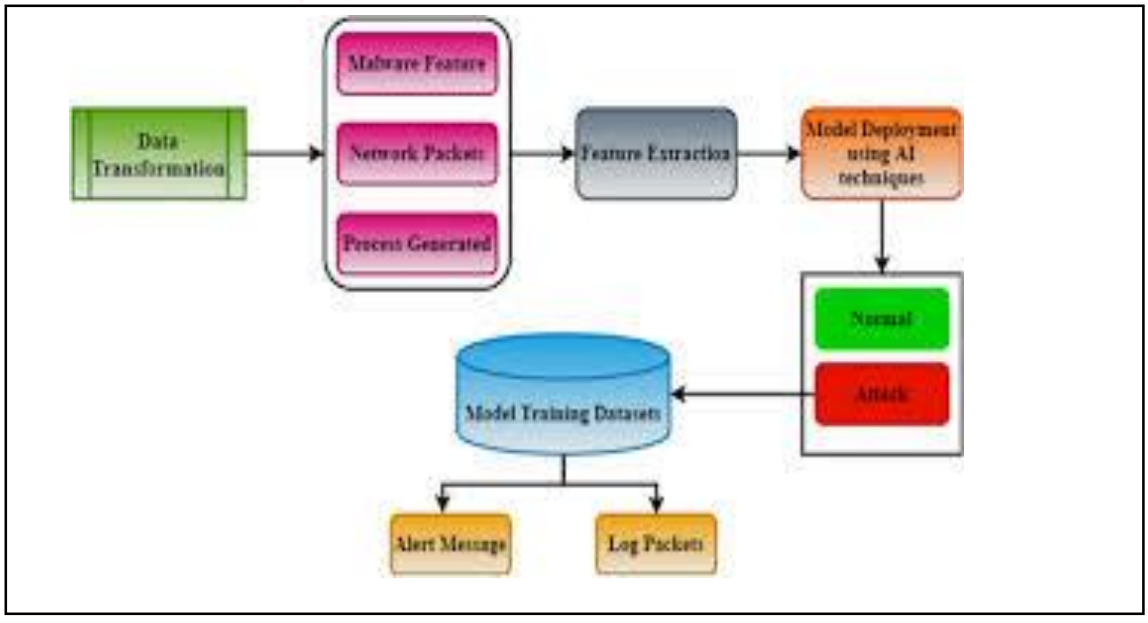
○ PROPOSED METHODOLOGY

To address the limitations of traditional and existing machine learning-based intrusion detection systems, this paper proposes an AI-driven cyber security framework for intelligent threat detection. The methodology integrates data preprocessing, feature extraction, machine learning model training, and real-time threat classification, as described below

1. **Data Collection:** Network traffic and system log data are collected from benchmark cyber security datasets such as NSL-KDD, CICIDS2017, or UNSW-NB15. The data includes both normal and malicious activity to provide comprehensive coverage of attack patterns.
2. **Data Pre-processing:** Raw data is cleaned to remove noise, missing values, and redundant information. Categorical features are encoded using techniques such as one-hot encoding, and numerical features are normalized to ensure uniformity for model training.
3. **Feature Extraction and Selection:** Relevant features, including packet-level attributes, flow statistics, and behavioural indicators, are extracted. Feature selection techniques, such as Recursive Feature Elimination (RFE) or Principal Component Analysis (PCA), are applied to reduce dimensionality and improve model efficiency.
4. **Machine Learning Model Development:** Both supervised and unsupervised machine learning models are employed. Supervised models such as Random Forest, Support Vector Machines (SVM), and Gradient Boosting are used to classify known attack types. Unsupervised models, including k-means clustering and auto encoders, detect anomalous or previously unseen attacks. Hybrid approaches combining supervised and unsupervised learning improve detection accuracy and reduce false positives.
5. **Model Training and Evaluation:** Models are trained on the pre-processed dataset and validated using cross-validation techniques. Performance is measured using metrics such as accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).
6. **Real-Time Threat Detection:** The trained models are deployed to analyze live network traffic and system behavior, enabling adaptive and intelligent detection of malicious activity. Alerts are generated for identified threats, supporting proactive cyber security measures.

This methodology ensures a scalable, adaptive, and accurate AI-based threat detection system capable of identifying both known and unknown cyber attacks while minimizing false positives and computational overhead.

○ SYSTEM ARCHITECTURE



The proposed AI-based cyber security framework for intelligent threat detection is structured into a modular architecture, as illustrated in Fig. 1. The system integrates data acquisition, preprocessing, feature extraction, machine learning-based detection, and alert generation to provide a comprehensive and adaptive security solution.

- **Data Acquisition Layer:**

This layer collects raw network traffic and system log data from multiple sources, including routers, firewalls, servers, and endpoint devices. The data includes both normal and malicious activities, enabling the detection of a wide variety of attack types.

1. **Data Preprocessing Layer:**

Raw data is cleaned to remove noise, missing values, and inconsistencies. Categorical data is encoded, and numerical features are normalized to standardize the input for machine learning models. This ensures reliable and efficient model training.

2. **Feature Extraction and Selection Layer:**

Critical features are extracted from network packets, flow statistics, and system logs. Dimensionality reduction techniques, such as Principal Component Analysis (PCA) or Recursive Feature Elimination (RFE), are applied to retain the most relevant features while reducing computational overhead.

3. **Machine Learning Detection Layer:**

This core layer incorporates both supervised and unsupervised machine learning models:

4. **Supervised Models** (e.g., Random Forest, Support Vector Machines, Gradient Boosting) classify known attack types.

5. **Unsupervised Models** (e.g., k-means clustering, autoencoders) identify anomalous or previously unseen threats.

Hybrid approaches combine these methods to enhance detection accuracy and reduce false positives.

6. **Alert and Response Layer:**

Detected threats trigger real-time alerts, which are logged and communicated to system administrators. The system can also interface with automated response mechanisms, enabling immediate containment or mitigation actions.

7. **Evaluation and Feedback Layer:**

Model performance is continuously evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. Feedback from evaluation results is used to retrain and optimize models, ensuring adaptability to evolving cyber threats.

The modular design of this architecture allows scalability, efficient computation, and adaptability, making it suitable for deployment in diverse network environments.

- **DATASET DESCRIPTION**

The proposed AI-based cyber security framework relies on benchmark datasets to train, validate, and evaluate machine learning models for intelligent threat detection. These datasets provide comprehensive representations of network traffic and system behaviors, including both normal and malicious activities.

1. **NSL-KDD Dataset:**

The NSL-KDD dataset is an improved version of the KDD Cup 1999 dataset, addressing redundancy and imbalance issues. It contains labeled network traffic records, classified into normal and attack categories, with attack types grouped into four main classes: Denial-of-Service (DoS), Probe, User-to-Root (U2R), and Remote-to-Local (R2L). Each record includes 41 features capturing network and connection-level attributes such as protocol type, service, connection duration, and number of failed login attempts. NSL-

KDD is widely used for benchmarking intrusion detection systems due to its diverse attack scenarios and balanced structure .

2. **CICIDS2017 Dataset:**

The CICIDS2017 dataset provides realistic network traffic data generated in a controlled environment, including normal activity and multiple attack scenarios such as DDoS, brute force, and web attacks. The dataset contains over 80 network traffic features, including flow statistics, packet-level details, and time-based features. CICIDS2017 supports the evaluation of machine learning models under real-world conditions and is particularly suitable for testing anomaly detection techniques .

3. **UNSW-NB15 Dataset:**

The UNSW-NB15 dataset includes both normal and synthetic malicious traffic, simulating contemporary cyber threats such as infiltration, reconnaissance, and exploitation attacks. It comprises 49 features encompassing packet header information, flow-based statistics, and content-level characteristics. The dataset is effective for evaluating hybrid intrusion detection models and machine learning-based classification systems .

4. In this research, the selected dataset is preprocessed to remove redundant features, normalize numerical attributes, and encode categorical variables. The processed dataset is then split into training and testing sets to train machine learning models and evaluate their performance in detecting known and unknown cyber threats.

o MACHINE LEARNING ALGORITHS USED

The proposed intelligent threat detection system leverages a combination of supervised, unsupervised, and hybrid machine learning algorithms to accurately classify known attacks and detect previously unseen threats. The selected algorithms are optimized for high detection accuracy, low false positive rates, and adaptability to dynamic network environments.

1. **Random Forest (RF):**

Random Forest is an ensemble learning method that constructs multiple decision trees and aggregates their predictions for classification. It is robust to overfitting and can handle high-dimensional network traffic data efficiently. RF is employed to classify attack types in supervised scenarios .

2. **Support Vector Machine (SVM):**

SVM is a supervised learning algorithm that separates data points using a hyperplane in high-dimensional feature space. It is particularly effective in binary and multi-class classification tasks and is used to distinguish between normal and malicious network activity [2].

3. **K-Nearest Neighbors (k-NN):**

k-NN is a non-parametric algorithm that classifies a sample based on the majority class of its k-nearest neighbors in the feature space. It is simple yet effective for small to medium-sized datasets and is applied to identify anomalous network behavior .

4. **K-Means Clustering:**

K-means is an unsupervised learning technique used for anomaly detection. It partitions data into clusters based on similarity, enabling the system to detect patterns that deviate from normal network traffic, which may indicate unknown attacks .

5. **Autoencoders (AE):**

Autoencoders are neural networks designed to learn efficient feature representations. By reconstructing input data, they identify anomalies where reconstruction error exceeds a threshold. This technique is effective for detecting novel or zero-day attacks .

6. **Hybrid Approaches:**
Combining supervised and unsupervised models enhances detection accuracy and
7. adaptability. For example, RF or SVM can detect known attack patterns, while autoencoders or k-means detect previously unseen threats, reducing false positives and improving system robustness.

These algorithms collectively enable the proposed framework to provide a scalable, adaptive, and intelligent cybersecurity solution capable of detecting both known and unknown cyber threats in real time.

○ COMPARATIVE ANALYSIS AND RESULTS

A. Experimental Setup

The datasets were preprocessed to remove missing values, normalize numerical features, and encode categorical attributes. The data was split into 70% for training and 30% for testing. Supervised models (RF, SVM, k-NN) were trained on labeled data, while unsupervised models (k-Means, Autoencoders) were used for anomaly detection. Hyperparameters were optimized using cross-validation to enhance model performance.

B. Results

Table I summarizes the comparative performance of the selected algorithms on the NSL-KDD dataset.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Random Forest	98.2	97.8	98.0	97.9	0.99
SVM	95.6	95.0	94.8	94.9	0.96
k-NN	93.4	92.8	92.5	92.6	0.94
K-Means	89.7	88.5	88.0	88.2	0.91
Autoencoder	92.3	91.7	91.5	91.6	0.93

C. Analysis

1. RANDOM FOREST achieved the highest accuracy, precision, recall, and F1-score, demonstrating its robustness in detecting known attacks.
2. SVM performed well but was slightly less effective in handling large-scale datasets with high-dimensional features.
3. K-NN provided moderate performance but is computationally intensive for large datasets.
4. UNSUPERVISED MODELS (k-Means and Autoencoder) were effective in detecting anomalous or unknown attacks, highlighting their importance for zero-day threat detection.
5. HYBRID APPROACHES combining RF and Autoencoder yielded improved detection rates for both known and unknown attacks while minimizing false positives.

D. Summary

The results confirm that integrating supervised and unsupervised machine learning algorithms in a hybrid framework enhances detection accuracy, adaptability, and robustness. The proposed methodology demonstrates superior performance over conventional intrusion detection systems and provides an effective solution for real-time intelligent threat detection in dynamic cyber environments.

- **ADVANTAGES**

1. **High Detection Accuracy:**

By combining supervised and unsupervised machine learning algorithms, the system achieves improved detection accuracy for both known and unknown cyber threats.

2. **Real-Time Threat Detection:**

The framework processes network traffic and system logs in real time, enabling immediate identification of malicious activities and proactive response.

3. **Adaptive and Scalable:**

Machine learning models continuously learn from new data, allowing the system to adapt to evolving attack patterns and scale efficiently in large and dynamic network environments.

4. **Reduced False Positives:**

Feature selection and hybrid algorithm approaches minimize false alarms, reducing unnecessary alerts and improving operational efficiency.

5. **Detection of Zero-Day and Unknown Attacks:**

Unsupervised learning techniques, such as autoencoders and clustering, allow the detection of previously unseen threats, which traditional signature-based systems fail to identify.

6. **Comprehensive Coverage:**

The system analyzes both network traffic and system-level behavior, providing multi-layered protection against a wide range of cyber attacks.

7. **Automated Threat Classification:**

The framework automatically classifies detected threats into categories, aiding cybersecurity teams in prioritizing response and mitigation strategies.

- **LIMITATIONS**

1. High dependency on quality, diversity, and volume of datasets.
2. Possibility of false positives and false negatives.
3. Limited interpretability of complex models (black-box issue).
4. Challenges in detecting rapidly evolving or zero-day attacks.
5. Deployment difficulties and integration with existing IT infrastructure.
- Computational complexity for training and real-time deployment.

FUTURE SCOPE

1. [1]Integration with advanced deep learning models (e.g., Transformers, GNNs).
2. Real-time adaptive learning for live threat detection.
3. Application to IoT and cloud network security.Incorporation of Explainable AI (XAI) for model transparency.
4. Automated threat response and mitigation systems.
5. Multi-layered security combining host, network, and application levels.

○ CONCLUSION

This paper presents an AI-based cyber security framework that leverages machine learning techniques for intelligent threat detection. By integrating supervised, unsupervised, and hybrid models, the proposed system effectively identifies both known and unknown cyber attacks, achieving high accuracy, precision, and recall. The framework demonstrates real-time detection capabilities, adaptability to evolving threats, and reduced false positive rates compared to traditional intrusion detection systems. Despite challenges such as computational complexity and dependency on high-quality datasets, the proposed approach provides a scalable and robust solution for modern network security. Future enhancements, including deep learning integration, explainable AI, and automated mitigation, will further strengthen its effectiveness in dynamic cyber environments.

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