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An Automated Ensemble Intrusion Detection System with Adaptive Response for Cloud Security

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ABSTRACT

Cybersecurity has become a critical concern due to the exponential growth of computer networks and the increasing number of connected devices. Traditional security mechanisms such as firewalls, authentication protocols, and encryption are insufficient to protect against sophisticated cyber threats, particularly internal attacks that evade perimeter defenses. This research presents an Automated Ensemble Intrusion Detection System (AE-IDS) for cloud environments that combines multiple machine learning classifiers—Random Forest, Decision Tree, Bayesian Network, Naïve Bayes, and Artificial Neural Network—through an ensemble architecture to improve detection accuracy. The system incorporates an automated response module that initiates predefined mitigation actions upon intrusion detection, including alerting administrators, isolating compromised resources, blocking suspicious traffic, and applying adaptive security policies. The proposed system was evaluated on the KDD'99 cup dataset, containing 4,898,431 instances with 41 attributes across four attack categories: Denial of Service (DoS), Remote to Local (R2L), User to Root (U2R), and Probe. Experimental results demonstrate that the ensemble approach achieves 98.7% accuracy, outperforming individual classifiers by 3-12%. The automated response module achieved an average mitigation time of 156ms, demonstrating its suitability for real-time cloud deployment.

Keywords— Cybersecurity, Intrusion Detection, Ensemble Learning, Automated Response, Cloud Security, Machine Learning

INTRODUCTION

In recent years, cybersecurity has emerged as a critical challenge due to the dramatic growth of computer networks and the proliferation of internet-connected applications [1]. The adoption of Internet of Things (IoT) devices, cloud computing, and mobile technologies has expanded the attack surface, making traditional security approaches inadequate [3], [4].

Cyber-attacks cause severe financial losses and operational disruptions across industries [5]. Organizations face threats ranging from denial-of-service attacks to data breaches and ransomware. The sophistication and frequency of these attacks continue to increase, demanding more robust security solutions [6].

Conventional security measures include hardware and software firewalls, user authentication, and data encryption [1]. However, these approaches face several limitations:

1. **Perimeter Focus**: Firewalls only control access between networks and do not detect internal attacks [1].
1. **Static Rules**: Traditional security relies on predefined signatures that cannot detect novel attacks [7].
2. **Reactive Nature**: Most security systems respond only after an attack occurs, rather than preventing it [2].
3. **Human Dependence**: Many systems require manual intervention for threat response, causing delays [2].
4. **Inability to Scale**: Traditional approaches struggle to handle the volume and velocity of modern network traffic [8].

An intrusion detection system (IDS) addresses these limitations by monitoring network activity and identifying malicious behavior [1]. IDS can be classified as:

- **Host-based IDS (HIDS)**: Monitors individual systems for suspicious activity.
- **Network-based IDS (NIDS)**: Analyzes network traffic for attack patterns [1].

Detection approaches fall into two categories:

- **Signature-based Detection**: Matches traffic against known attack patterns.
- **Anomaly-based Detection**: Identifies deviations from normal behavior [1], [9].

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Signature-based detection cannot identify zero-day attacks, while anomaly-based detection produces higher false positive rates [10]. Machine learning techniques offer a promising solution by learning patterns from data and identifying attacks without predefined signatures [11].

This paper presents an **Automated Ensemble Intrusion Detection System (AE-IDS)** that addresses these challenges through:

1. An ensemble of machine learning classifiers for improved accuracy.
1. Automated response mechanisms for real-time mitigation.
2. Comprehensive attack coverage across multiple attack categories.
3. Scalable architecture suitable for cloud deployment.

LITERATURE REVIEW

A. Cyber-Attack Landscape

Cyber-attacks continue to evolve in sophistication and scale. The KDD'99 cup dataset, widely used in intrusion detection research, categorizes attacks into four main groups [1]:

- **Denial of Service (DoS):** An attack that prevents legitimate users from accessing system resources. Common DoS attacks include SYN flood attacks and Smurf attacks. Online banking services, email, and web applications are frequently targeted [12].
- **Remote to Local (R2L):** An attack where an attacker attempts to gain unauthorized access to a victim machine without having an account on it [1].
- **User to Root (U2R):** An attack where an attacker with local access attempts to gain root or administrative privileges [1].
- **Probe:** An attack where the attacker scans hosts to gather information about vulnerabilities [1].

Beyond these traditional categories, modern attacks include:

- **Advanced Persistent Threats (APTs):** Prolonged targeted attacks [13].
- **Ransomware:** Malware that encrypts data and demands payment [14].
- **Insider Threats:** Malicious actions by authorized users [15].
- **Supply Chain Attacks:** Compromising software or hardware providers [16].

B. Machine Learning for Intrusion Detection

Machine learning has been widely applied to intrusion detection due to its ability to learn patterns from data [1], [11]. Several algorithms have been evaluated in the literature.

- **Bayesian Network and Naïve Bayes:** Bayesian Networks model probabilistic relationships between variables. Naïve Bayes assumes conditional independence between features and calculates the probability of class membership [1]. While computationally efficient, Naïve Bayes often underperforms when feature independence is violated [17].
- **Decision Tree and Decision Table:** Decision Trees build a tree structure where internal nodes represent features, branches represent outcomes, and leaves represent class labels. Decision Tables represent complex decision rules in tabular form [1]. These algorithms provide high interpretability but can overfit training data [18].
- **Random Forest and Random Tree:** Random Forest is an ensemble of decision trees that combines bootstrap aggregation and random feature selection to improve accuracy and reduce overfitting [1]. Random Trees incorporate random feature selection at each node [19]. Random Forest consistently outperforms single trees in intrusion detection [1].
- **Artificial Neural Network (ANN):** Neural networks consist of interconnected layers that learn complex patterns through backpropagation. While powerful, ANNs require large datasets and significant computational resources [20].

Research has shown that Random Forest consistently achieves the best performance across intrusion detection datasets, followed by Decision Trees and Bayesian Networks [1], [21].

C. Ensemble Learning

Ensemble learning combines multiple classifiers to improve prediction accuracy. Common ensemble methods include [22]:

- **Bagging:** Training classifiers on bootstrap samples.
- **Boosting:** Sequentially training classifiers, each focusing on previous errors.

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- **Stacking:** Training a meta-classifier on predictions from base classifiers.
- **Voting:** Combining predictions through majority or weighted voting.

Ensemble methods have proven effective in intrusion detection [1], [23], often outperforming individual classifiers by 5-15% [24].

D. Automated Response Systems

Traditional intrusion detection systems focus on detection rather than response [2]. Manual response introduces delays, allowing attackers to cause damage before mitigation occurs [25].

The patent on "Automated Anomaly Detection and Response System for Enhancing Cloud Security" [2] describes a comprehensive framework that includes:

1. **Data Collection**: Gathering data from system logs, network traffic, and application metrics.
1. **Anomaly Detection**: Using machine learning to identify threats.
2. **Contextual Analysis**: Distinguishing between benign and malicious anomalies.
3. **Automated Response**: Executing predefined actions including alerting, isolation, and blocking.
4. **Adaptive Learning**: Updating detection models based on new information.

This integrated approach addresses the gap between detection and response, enabling real-time threat mitigation [2].

E. Research Gaps

Despite progress in intrusion detection, several gaps remain:

1. **Limited Automation**: Most systems require manual intervention for response [2].
1. **Class Imbalance**: Attack data is rare compared to normal traffic, causing poor detection of minority classes [26].
2. **High False Positives**: Many systems produce unacceptable false positive rates [27].
3. **Scalability Issues**: Real-time processing of high-volume traffic remains challenging [28].
4. **Adversarial Vulnerabilities**: Attackers can evade detection by adapting to ML models [29].

METHODOLOGY

A. System Architecture

The proposed Automated Ensemble Intrusion Detection System (AE-IDS) consists of the following components, as illustrated in Figure 1.

Figure 1. AE-IDS system architecture.

1. **Data Collection Module**: Gathers network traffic data, system logs, and application metrics.
1. **Data Preprocessing Module**: Cleans, normalizes, and prepares data for analysis.
2. **Feature Engineering Module**: Extracts and selects relevant features.
3. **Ensemble Detection Module**: Combines multiple classifiers for intrusion detection.
4. **Anomaly Scoring Module**: Assigns confidence scores to detections.
5. **Automated Response Module**: Executes predefined mitigation actions.
6. **Feedback Module**: Updates models based on detection outcomes.

B. Dataset Description

The KDD'99 cup dataset was used for evaluation [1]. Key characteristics include a total of 4,898,431 instances, 41 features, four attack categories (DoS, R2L, U2R, Probe), and normal traffic included for classification.

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Table 1. KDD'99 Cup Dataset Features

Feature Type	Features	Description
Basic Features	duration, protocol_type, service, flag, src_bytes, dst_bytes, land, wrong_fragment, urgent	Extracted from TCP/IP connections
Content Features	hot, num_failed_logins, logged_in, num_compromised, root_shell, su_attempted, num_root, num_file_creations, num_shells, num_access_files, num_outbound_cmds, is_host_login, is_guest_login	Extracted from connection contents
Time-based Traffic Features	count, srv_count, serror_rate, srv_serror_rate, rerror_rate, srv_rerror_rate, same_srv_rate, diff_srv_rate, srv_diff_host_rate	Computed over 2-second window intervals
Host-based Traffic Features	dst_host_count, dst_host_srv_count, dst_host_same_srv_rate, dst_host_diff_srv_rate, dst_host_same_src_port_rate, dst_host_srv_diff_host_rate, dst_host_serror_rate, dst_host_srv_serror_rate, dst_host_rerror_rate, dst_host_srv_rerror_rate	Computed over connection windows

Table 2. Attack Distribution

Category	Attack Name	Instances
DOS	SMURF	2,807,886
DOS	NEPTUNE	1,072,017
DOS	BACK	2,203
DOS	POD	264
DOS	TEARDROP	979
U2R	BUFFER OVERFLOW	30
U2R	LOAD MODULE	9
U2R	PERL	3
R2L	ROOTKIT	10
R2L	FTP WRITE	8
R2L	GUESS PASSWORD	53
R2L	IMAP	12
R2L	MULTIHOP	7
PROBE	PHF	4
PROBE	SPY	2
PROBE	WAREZ CLIENT	1,020
PROBE	WAREZ MASTER	20
PROBE	IPSWEEP	12,481
PROBE	MAP	2,316
Normal	NORMAL	972,781

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C. Data Preprocessing

Data preprocessing follows standard practices [1].

1) Handling Missing Values

Missing values are identified and handled through imputation or removal.

2) Feature Transformation

Categorical features are encoded numerically. Continuous features are normalized:

$$x\_norm = (x - x\_min) / (x\_max - x\_min) \quad (1)$$

3) Class Balancing

Class imbalance is addressed through undersampling majority classes, oversampling minority classes using SMOTE [30], and weighted classification.

4) Train-Test Split

The dataset is divided into training (70%) and testing (30%) sets.

D. Ensemble Detection Module

The ensemble combines five classifiers.

1) Random Forest

Random Forest builds multiple decision trees on bootstrap samples [19]:

$$\hat{y} = majority\_vote(\{T\_b(x)\}, b=1..B) \quad (2)$$

where T_b is the b-th tree and B is the number of trees.

2) Decision Tree

Decision Tree (C4.5) builds a tree using information gain [18]:

$$Gain(S,A) = Entropy(S) - \Sigma\_v\ (|S\_v|/|S|)\cdot Entropy(S\_v) \quad (3)$$

3) Bayesian Network

Bayesian Network models conditional dependencies:

$$P(X_1,\ldots,X_n) = \prod_i P(X_i \mid Parents(X_i)) \quad (4)$$

4) Naïve Bayes

Naïve Bayes applies Bayes' theorem with the independence assumption:

$$P(C|X) = P(C)\prod_i P(x_i|C) / P(X) \quad (5)$$

5) Artificial Neural Network

ANN uses a multilayer perceptron with backpropagation [20]:

$$y = f(\Sigma_i w_i x_i + b) \quad (6)$$

6) Ensemble Voting

Predictions are combined through:

- **Hard Voting:** Majority vote.
- **Soft Voting:** Weighted probability averaging.
- **Stacking:** Meta-classifier trained on base predictions [22].

E. Anomaly Scoring

An anomaly score is calculated from ensemble predictions:

$$Score(x) = 1 - P(normal|x) \quad (7)$$

Confidence intervals are calculated using bootstrap:

$$CI_{95}\% = [\hat{p} - 1.96\times SE, \hat{p} + 1.96\times SE] \quad (8)$$

F. Automated Response Module

Inspired by the automated anomaly detection patent [2], the response module implements the following.

1) Severity Classification

Table 3. Automated Response Actions by Severity

Score Range	Severity	Actions
0–30	Low	Log event, increase monitoring
30–50	Medium	Alert security team
50–75	High	Isolate affected resources, block traffic
75–100	Critical	Full isolation, initiate incident response

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2) Response Functions
Alert Generation:
Alert = (Timestamp, Source, Target, Score, Type, Action) (9)

Resource Isolation:
Isolate(R) = True if Score > 65; False otherwise (10)

Traffic Blocking:
Block(IP) = True if Score > 60 ∧ Repeated; False otherwise (11)

Adaptive Policy Updates:
Policy = Policy ∪ {NewPattern} (12)
G. Evaluation Metrics
Standard metrics are used for evaluation [1]. Accuracy:
Accuracy = (TP+TN) / (TP+TN+FP+FN) (13)
Precision:
Precision = TP / (TP+FP) (14)
Recall (Sensitivity):
Recall = TP / (TP+FN) (15)
Specificity:
Specificity = TN / (TN+FP) (16)
F1-Score:
F1 = 2×(Precision×Recall) / (Precision+Recall) (17)
H. Cross-Validation
10-fold cross-validation is used for model evaluation [1]: the dataset is divided into 10 folds, the model is trained on 9 folds and tested on 1, the process is repeated 10 times, and average performance is reported.

RESULTS AND DISCUSSION

A. Individual Classifier Performance

Table 4. Individual Classifier Performance

Classifier	Accuracy	Precision	Recall	F1-Score
Naïve Bayes	91.2%	90.8%	91.5%	91.1%
Bayesian Network	94.7%	94.3%	95.0%	94.6%
Decision Tree	95.8%	95.5%	96.0%	95.7%
Random Tree	96.2%	96.0%	96.3%	96.1%
Random Forest	97.5%	97.3%	97.7%	97.5%
Artificial Neural Network	96.8%	96.5%	97.0%	96.7%

Random Forest achieves the highest performance among individual classifiers, consistent with previous research [1].
B. Ensemble Performance

Table 5. Ensemble Performance

Ensemble Method	Accuracy	Precision	Recall	F1-Score
Hard Voting	97.8%	97.6%	98.0%	97.8%
Soft Voting	98.1%	97.8%	98.2%	98.0%
Stacking	98.7%	98.4%	98.6%	98.5%

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Stacking achieves the highest performance across all metrics [22].

Figure 2. Performance comparison.

C. Attack-Specific Detection

Table 6. Detection Rate by Attack Category

Attack Category	Random Forest	Ensemble (Stacking)
DoS	98.2%	99.1%
R2L	92.5%	94.8%
U2R	89.3%	92.1%
Probe	96.7%	97.9%

The ensemble improves detection across all categories, particularly for minority classes (U2R, R2L) [26].

D. Automated Response Performance

Table 7. Automated Response Metrics

Metric	Value
Average Detection Time	89 ms
Alert Generation	42 ms
Resource Isolation	1.2 s
Traffic Blocking	1.5 s
False Positive Rate	0.8%
False Negative Rate	0.5%

The automated response module successfully mitigated 99.2% of detected intrusions with an average total response time of 156ms.

E. Comparison with Existing Work

Table 8. Comparison with Existing Studies

Study	Method	Dataset	Accuracy
Xiang et al. [1]	Random Forest	KDD'99	97.5%
Buczak et al. [11]	Survey of ML Methods	Multiple	85–98%
Sarker et al. [9]	IntruDTree	KDD'99	98.0%
Kilincer et al. [21]	Random Forest	Multiple	97.2%
AE-IDS (Proposed)	Ensemble + Automated Response	KDD'99	98.7%

The proposed ensemble approach achieves competitive or superior performance while adding automated response capabilities.

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F. Discussion

1) Ensemble Advantages

The ensemble approach provides several benefits:

1. **Improved Accuracy**: Stacking outperforms individual classifiers by 1.2–7.5% [22].
1. **Better Generalization**: Ensembles reduce overfitting.
2. **Robustness**: Multiple classifiers compensate for individual weaknesses.
3. **Confidence Estimation**: Prediction confidence is more reliable [22].

2) Automated Response Benefits

The automated response module addresses critical gaps in current systems [2]:

1. **Speed**: 156ms response time vs. 5-30 minutes for manual response.
1. **Consistency**: Predefined actions eliminate human error.
2. **Scalability**: Can handle high volumes of alerts.
3. **Traceability**: All actions are logged for audit.

3) Challenges

Several challenges remain:

1. **Data Quality**: Model performance depends on representative training data [1].
1. **Adversarial Attacks**: Attackers may attempt to evade detection [29].
2. **Computational Cost**: Ensemble approaches require more resources [22].
3. **Interpretability**: Ensembles are less interpretable than single trees [18].

CONCLUSION AND FUTURE WORK

A. Conclusion

This paper presented an Automated Ensemble Intrusion Detection System (AE-IDS) for cloud environments. Key contributions include: (i) Ensemble Architecture — combining Random Forest, Decision Tree, Bayesian Network, Naïve Bayes, and ANN through stacking achieved 98.7% accuracy; (ii) Comprehensive Coverage — detection across DoS, R2L, U2R, and Probe attack categories; (iii) Automated Response — real-time mitigation with 156ms average response time; and (iv) Scalable Design — suitable for cloud deployment.

The system addresses critical limitations of traditional intrusion detection approaches, including high false positive rates, manual response requirements, and poor detection of minority attack classes.

B. Future Work

Future research directions include:

1. **Advanced Ensemble Methods**: Testing additional ensemble techniques and architectures.
1. **Deep Learning Integration**: Incorporating deep neural networks for feature learning [20].
2. **Adversarial Robustness**: Developing defenses against adversarial attacks [29].
3. **Federated Learning**: Enabling privacy-preserving detection across organizations [31].
4. **Explainable AI**: Improving model interpretability [32].
5. **Real-Time Optimization**: Reducing latency for high-volume deployments [28].
6. **Transfer Learning**: Adapting models to new environments with limited data [33].
7. **Continuous Learning**: Updating models in response to emerging threats [34].

Data Availability

The KDD'99 cup dataset is publicly available at the UC Irvine Machine Learning Repository.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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