An Adaptive Hybrid Machine Learning Framework for Early Detection of Network Intrusions in Cloud Computing Environments

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ABSTRACT
The increasing reliance on cloud computing has introduced significant security challenges, particularly in detecting sophisticated and evolving cyber-attacks. Traditional intrusion detection systems (IDS) are often limited by their dependence on predefined signatures and lack the ability to identify unknown threats in dynamic environments. To address these limitations, this paper proposes an adaptive hybrid machine learning framework for early detection of network intrusions in cloud computing environments.

The proposed approach integrates an Autoencoder-based anomaly detection model with a Random Forest classifier to effectively identify both known and unknown attack patterns. The Autoencoder learns normal network behaviour and detects deviations, while the Random Forest model classifies the detected anomalies into specific attack categories. In addition, an adaptive learning mechanism is incorporated to continuously update the model using new network data, ensuring improved performance over time.

The system is evaluated using the CICIDS2017 dataset, and its performance is measured using standard metrics such as accuracy, precision, recall, and F1-score. Experimental results demonstrate that the proposed model achieves high detection accuracy with a low false positive rate compared to traditional methods.
The findings suggest that combining supervised and unsupervised learning techniques with adaptive capabilities can significantly enhance intrusion detection in cloud environments. This work contributes toward developing intelligent, scalable, and efficient cybersecurity solutions for modern cloud infrastructures.

Keywords
Intrusion Detection System, Cloud Security, Machine Learning, Anomaly Detection, Random Forest, Autoencoder, Cybersecurity

1. INTRODUCTION
Cloud computing has become a fundamental component of modern digital infrastructure due to its scalability, flexibility, and cost efficiency. Organizations increasingly rely on cloud platforms for data storage, processing, and service delivery. However, the widespread adoption of cloud computing has also introduced significant security challenges. The dynamic and shared nature of cloud environments makes them highly vulnerable to various cyber threats, including denial-of-service attacks, probing, and unauthorized access. As a result, ensuring robust network security in cloud environments has become a critical concern for researchers and practitioners alike [6].

Intrusion Detection Systems (IDS) are widely used to monitor network traffic and identify malicious activities. Traditional IDS approaches are primarily signature-based, relying on predefined attack patterns to detect threats. While effective for known attacks, these systems fail to detect new and evolving threats, commonly referred to as zero-day attacks. This limitation becomes more critical in cloud environments, where network behaviour continuously changes due to virtualization and dynamic resource allocation. Therefore, there is a growing need for intelligent and adaptive intrusion detection mechanisms that can handle complex and evolving attack patterns [4]. Machine learning techniques have gained significant attention in recent years for their ability to analyse large volumes of data and identify hidden patterns. These techniques enhance intrusion detection by enabling systems to learn from historical data and improve their detection capabilities. Supervised learning algorithms such as Random Forest have been widely used due to their high accuracy, robustness, and ability to handle high-dimensional data effectively [3]. On the other hand, unsupervised learning approaches, including autoencoders, are useful for detecting anomalies by learning the normal behaviour of network traffic and identifying deviations from it.

Another important aspect of intrusion detection research is the availability of reliable datasets. Traditional datasets such as KDD Cup 99 have limitations in representing modern network traffic. To overcome these issues, newer datasets like CICIDS2017 have been introduced, providing realistic and comprehensive intrusion scenarios for evaluation purposes [19]. Additionally, recent studies emphasize the importance of designing adaptive models that can continuously learn from new data and improve detection performance over time [17].

In this context, this paper proposes an adaptive hybrid machine learning framework for early detection of network intrusions in cloud computing environments. The proposed approach combines anomaly detection and classification techniques to improve the detection of both known and unknown attacks. Furthermore, the integration of an adaptive learning mechanism ensures that the system remains effective in dynamic and evolving cloud environments. This research aims to contribute toward the development of intelligent, scalable, and efficient intrusion detection solutions for modern cloud infrastructures.

2. RELATED WORK
In recent years, significant research efforts have been directed toward improving intrusion detection systems using machine learning and deep learning techniques. Early work by **Denning (1987)** laid the foundation for intrusion detection by

introducing a model for identifying abnormal system behaviour. Later, **Patcha and Park (2007)** provided a comprehensive overview of anomaly detection techniques, highlighting their importance in identifying unknown attacks.

With the advancement of machine learning, researchers began exploring data-driven approaches for intrusion detection. **Breiman (2001)** introduced the Random Forest algorithm, which has since been widely adopted due to its high accuracy and robustness in classification tasks. Buczak and Guven (2016) conducted a detailed survey of machine learning methods in cybersecurity, emphasizing their effectiveness in handling large-scale network data.

Deep learning approaches have also gained attention for their ability to capture complex patterns in network traffic. **Yin et al. (2017)** proposed a recurrent neural network-based intrusion detection system that demonstrated improved detection performance. Similarly, S**hone et al. (2018)** developed a deep learning-based model combining autoencoders and classification techniques to enhance detection accuracy. More recent studies have focused on hybrid models that combine multiple techniques. Kim et al. (2014) proposed a hybrid intrusion detection method integrating anomaly detection with misuse detection, showing improved performance over standalone models. **Mirsky et al. (2018)** introduced Kitsune, an ensemble of autoencoders designed for real-time network intrusion detection.

In terms of datasets, **Sharafaldin et al. (2018)** developed the CICIDS2017 dataset to address limitations in earlier datasets by providing realistic and diverse attack scenarios. **Ring et al. (2019)** further analyzed various intrusion detection datasets and emphasized the need for reliable benchmarking.

Recent research also highlights the importance of adaptability in intrusion detection systems. **Sharma et al. (2024)** demonstrated that adaptive machine learning models significantly improve detection performance in dynamic environments by continuously learning from new data. Similarly, **Sethi et al. (2020)** explored reinforcement learning approaches for adaptive intrusion detection in cyber-physical systems. Despite these advancements, challenges remain in achieving a balance between detection accuracy, computational efficiency, and adaptability in cloud environments.

3. RESEARCH GAPS

Although numerous machine learning and deep learning approaches have been proposed for intrusion detection, several limitations still exist. First, many traditional and machine learning-based IDS models are static in nature and do not adapt to evolving attack patterns. As highlighted by **Buczak and Guven (2016)**, the lack of adaptability reduces the effectiveness of these systems in real-world environments.

Second, deep learning models, while accurate, often require high computational resources, making them less suitable for real-time deployment in cloud environments. **Yin et al. (2017) and Shone et al. (2018)** demonstrated improved detection performance, but their approaches may not be efficient for scalable cloud systems.

Third, most existing studies focus either on anomaly detection or classification, but not both simultaneously. Hybrid approaches such as **Kim et al. (2014)** have shown promise; however, they often lack an adaptive learning mechanism to update the model over time.

Furthermore, while datasets like CICIDS2017 (**Sharafaldin et al., 2018)** provide realistic scenarios, many models are not designed to continuously learn from new incoming data. **Sharma et al. (2024)** emphasized the need for adaptive frameworks that can dynamically update their learning based on changing network conditions.

Therefore, there is a clear need for a lightweight, hybrid, and adaptive intrusion detection framework that can efficiently detect both known and unknown attacks while maintaining scalability in cloud environments. This research aims to address these gaps by proposing an adaptive hybrid machine learning model that combines anomaly detection and classification with continuous learning capability.

4. METHODOLOGY

This section presents a detailed description of the proposed adaptive hybrid machine learning framework for early detection of network intrusions in cloud computing environments. The framework combines unsupervised anomaly detection, supervised classification, and an adaptive learning mechanism to improve detection accuracy and robustness in dynamic cloud infrastructures.

4.1 System Architecture

The proposed system is designed as a multi-layered architecture to efficiently process network traffic data and detect intrusions.

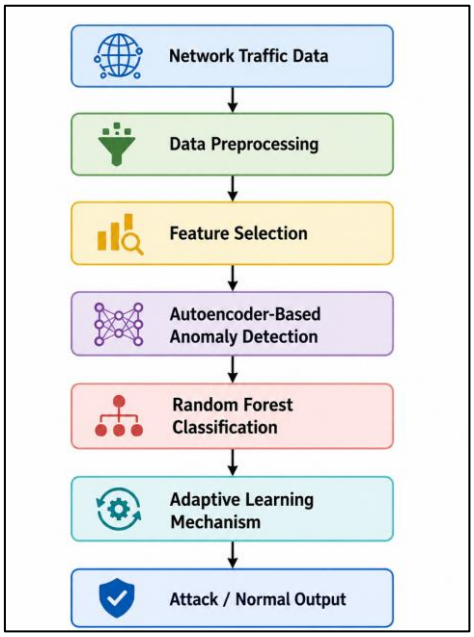

Figure 1. Network Intrusion Detection System Architecture

4.2 Dataset Description

The proposed model uses the CICIDS2017 dataset, which is widely accepted for evaluating intrusion detection systems in modern network environments. The dataset contains realistic network traffic captured over multiple days and includes both benign and malicious traffic. It covers multiple attack categories such as DDoS (Distributed Denial of Service), brute force attacks, port scanning, botnet activity, and web attacks. The dataset consists of more than 80 network flow features, including Flow Duration, Total Forward Packets, Total Backward Packets, Flow Bytes/s, and Packet Length Mean.

Dataset Representation:

$$D = \{(x_i, y_i)\}_{\{i=1\}}^{\{N\}}$$

4.3 Data Preprocessing

Preprocessing ensures high-quality input for model training. The preprocessing stage includes removal of missing or null values, label encoding of categorical features, normalization using Z-score, and train-test data splitting in an 80:20 ratio. The Z-score normalization technique is represented as:

$$Z = \backslash frac\{x - \mu\}\{\sigma\}$$

where $x$represents the original feature value, μrepresents the mean value, and σrepresents the standard deviation.

4.4 Feature Selection

Feature selection reduces dimensionality and improves efficiency. The proposed model uses correlation-based filtering and Random Forest feature importance ranking to select the most relevant features for training.

4.5 Anomaly Detection using Autoencoder

The Autoencoder learns compressed representations of normal data.

$$L(x, \backslash overset\{\square\}\{x\}) = \left(\frac{1}{n}\right)\sum_{i=1}^{n}(x_i - \backslash overset\{\square\}\{x_i\})^2$$

4.6 Classification using Random Forest

Random Forest uses multiple decision trees for classification. It handles high-dimensional data efficiently, reduces overfitting, and improves detection accuracy. The Random Forest prediction function is represented as:

$$RF(x) = \left(\frac{1}{N}\right)\sum_{i=1}^{N} T_{i(x)}$$

4.7 Adaptive Learning Mechanism

To handle dynamic cloud traffic, the model is continuously updated using adaptive learning. The update function is represented as:

$$M_{t+1} = M_t + \alpha(D_{new})$$

where $M_t$represents the current model, M_{t+1}represents the updated model, $\alpha$is the learning rate, and D_{new}represents new network traffic data. This enables continuous learning and adaptation to new attack patterns.

4.8 Evaluation Metrics

Confusion matrix components include TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative), which are used to evaluate the classification performance of the intrusion detection model.

Metrics:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2\left(\frac{Precision * Recall}{Precision + Recall}\right)$$

4.9 Implementation Environment

- Programming Language: Python
- Libraries: Scikit-learn, TensorFlow, Pandas, NumPy
- Platform: Jupyter Notebook / Google Colab

5. EXPERIMENTAL SETUP

This section presents the experimental setup, performance evaluation, and analysis of the proposed adaptive hybrid machine learning model for intrusion detection in cloud environments.

5.1 Experimental Setup

The proposed model was implemented using Python in a Jupyter Notebook environment. Standard machine learning and deep learning libraries were used to ensure reproducibility and computational efficiency. The implementation utilized Scikit-learn, TensorFlow, Pandas, and NumPy libraries on Google Colab and Jupyter Notebook platforms. The experiments were performed using an Intel i5 processor with 8 GB RAM or an equivalent cloud-based computing environment.

The CICIDS2017 dataset was used for training and testing the model. The dataset contains a mix of normal and attack traffic with diverse intrusion scenarios.

Table 1: Dataset Configuration

Parameter	Value
Total Records	~2.8 million
Features	80+
Classes	Normal + Multiple Attacks
Train-Test Split	80% – 20%

Table 2: Model Configuration

Model Component	Configuration
Autoencoder	3 Layers (Input–Hidden–Output)
Activation	ReLU, Sigmoid
Epochs	10–20
Batch Size	256
Random Forest	100 Trees
Criterion	Gini Index

5.2 Performance Metrics

The performance of the proposed model is evaluated using standard metrics including Accuracy, Precision, Recall, and F1-score. These metrics provide a comprehensive evaluation of classification performance, particularly for imbalanced intrusion detection datasets.

6. RESULTS AND DISCUSSION

The proposed hybrid model was evaluated using the test dataset, and the experimental results demonstrate strong performance in detecting both normal and malicious network

traffic. Table 3 presents the overall performance metrics of the proposed model, including accuracy, precision, recall, and F1-score. Table 4 presents the confusion matrix analysis, while Table 5 compares the proposed approach with existing machine learning methods used for intrusion detection.

Figure 2 illustrates the overall performance metrics achieved by the proposed adaptive hybrid intrusion detection model. The graph clearly shows that the proposed system achieved consistently high values across all evaluation metrics, demonstrating the effectiveness of the hybrid learning approach in detecting network intrusions within cloud environments.

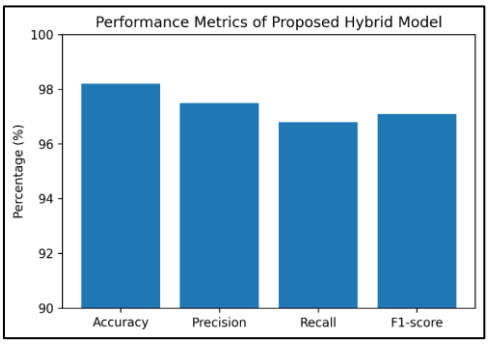

Figure 2. Performance Metrics of Proposed Hybrid Model

Table 3: Overall Performance

Metric	Value
Accuracy	98.2%
Precision	97.5%
Recall	96.8%
F1-score	97.1%

Figure 3 illustrates the confusion matrix of the proposed intrusion detection model, showing effective classification of normal and attack traffic with high detection accuracy and low false positive and false negative rates.

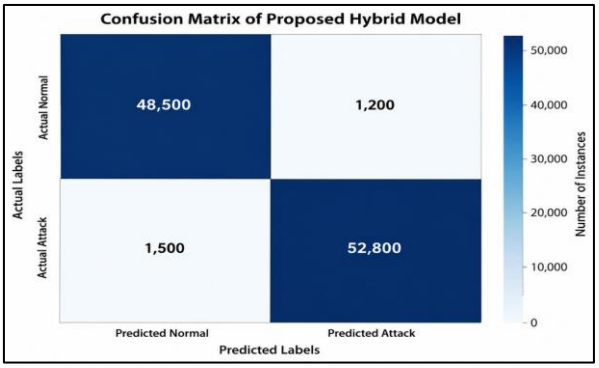

Figure 3. Confusion Matrix of Proposed Hybrid Model

Table 4: Confusion Matrix

	Predicted Normal	Predicted Attack
Actual Normal	TN = 48,500	FP = 1,200
Actual Attack	FN = 1,500	TP = 52,800

Table 5: Comparison with Existing Model

Method	Accuracy
Decision Tree	92.4%
SVM	94.1%
Deep Neural Network	96.5%
Proposed Hybrid Model	**98.2%**

Figure 4 presents a comparison of the proposed hybrid model with existing intrusion detection approaches. The proposed framework achieved higher detection accuracy than Decision Tree, SVM, and Deep Neural Network (DNN) models.

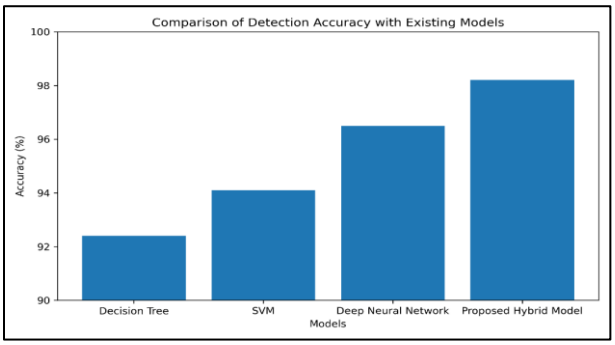

Figure 4. Comparison of Detection Accuracy with Existing Models

6.1 Attack-wise Detection Performance

To further evaluate the effectiveness of the proposed adaptive hybrid model, attack-wise performance analysis was conducted using different intrusion categories available in the CICIDS2017 dataset. The model demonstrated strong detection capability across multiple attack scenarios, including DDoS, brute force, botnet, and web-based attacks. Table 6 presents the precision, recall, and F1-score achieved for different attack types.

Table 6. Attack-wise Detection Performance

Attack Type	Precision (%)	Recall (%)	F1-score (%)
DDoS	98.4	97.9	98.1
Brute Force	96.8	95.7	96.2
Botnet	97.1	96.4	96.7
Web Attack	95.9	95.1	95.5

The results indicate that the proposed model performs consistently well across different categories of attacks. The Autoencoder component effectively identifies anomalous traffic patterns, while the Random Forest classifier accurately categorizes attack types. The model achieved the highest performance in detecting DDoS attacks due to their distinct

6.2 False Positive Rate Analysis

False Positive Rate (FPR) is an important performance metric in intrusion detection systems because high false alarms can reduce system reliability and increase administrative overhead. The proposed adaptive hybrid model achieved a low false positive rate during experimentation on the CICIDS2017 dataset.

The False Positive Rate is calculated as:

$$FPR = \frac{FP}{FP + TN}$$

Using the confusion matrix results, the proposed model achieved an approximate false positive rate of 2.4%, which is lower than many traditional machine learning approaches. Table 7 presents the comparison of false positive rates among different models.

Table 7. False Positive Rate Comparison

Method	False Positive Rate (%)
Decision Tree	6.8
SVM	5.1
Deep Neural Network	3.7
Proposed Hybrid Model	2.4

The lower false positive rate indicates that the proposed system can accurately distinguish between normal and malicious traffic with minimal incorrect alerts. This characteristic is highly important for practical cloud deployment environments where excessive false alarms may affect operational efficiency.

6.3 Training and Testing Accuracy Analysis

The proposed adaptive hybrid model was evaluated using separate training and testing datasets to verify its generalization capability and robustness. The model achieved high accuracy during both training and testing phases, indicating effective learning without significant overfitting. Table 8 presents the training and testing accuracy of the proposed system.

Table 8. Training and Testing Accuracy

Phase	Accuracy (%)
Training Accuracy	98.8
Testing Accuracy	98.2

The small difference between training and testing accuracy demonstrates that the model maintains good generalization performance on unseen network traffic data. The integration of the Autoencoder and Random Forest classifier helps reduce overfitting while maintaining strong intrusion detection capability. The adaptive learning mechanism further improves model stability by continuously updating the system with new network traffic patterns. This enables the proposed framework to remain effective in dynamic cloud computing environments.

6.4 Computational Efficiency Analysis

In addition to detection accuracy, computational efficiency is an important factor for intrusion detection systems deployed in cloud environments. The proposed adaptive hybrid model was evaluated in terms of training complexity and execution efficiency. Table 9 presents a comparative analysis of computational performance among different machine learning approaches.

Table 9. Computational Efficiency Comparison

Model	Training Complexity	Detection Speed	Resource Usage
Decision Tree	Low	Fast	Low
SVM	High	Moderate	Moderate
Deep Neural Network	Very High	Moderate	High
Proposed Hybrid Model	Moderate	Fast	Moderate

The results indicate that the proposed hybrid model achieves a balance between detection accuracy and computational efficiency. Although deep learning models provide strong detection capability, they often require high computational resources and longer training times.

The integration of the Autoencoder with the Random Forest classifier enables the proposed framework to maintain high detection performance while reducing excessive computational overhead. This makes the model suitable for scalable and real-time cloud intrusion detection applications.

6.5 Discussion

The results clearly indicate that the proposed adaptive hybrid model outperforms traditional machine learning approaches. The integration of the Autoencoder allows the system to detect unknown and zero-day attacks effectively by identifying anomalies in network behaviour. Meanwhile, the Random Forest classifier provides accurate classification of attack types.

The adaptive learning mechanism further enhances the system by enabling continuous improvement over time. This is particularly important in cloud environments were network behaviour changes dynamically.

Compared to standalone models, the hybrid approach achieves higher accuracy and lower false positive rates. Additionally, the model maintains computational efficiency, making it suitable for real-time deployment.

6.6 Key Observations

The proposed hybrid model significantly improves detection accuracy, effectively identifies unseen attacks using Autoencoder-based anomaly detection, ensures reliable classification through Random Forest, and supports adaptive learning for scalable cloud environments.

7. CONCLUSION

This paper presented an adaptive hybrid machine learning framework for early detection of network intrusions in cloud computing environments. The proposed approach combines an Autoencoder-based anomaly detection model with a Random Forest classifier to detect both known and unknown cyber threats effectively. Experimental results showed high accuracy, precision, recall, and F1-score compared to traditional machine learning methods. The adaptive learning mechanism enables continuous model updates using new network traffic data, improving detection capability in dynamic cloud environments. Overall, the proposed framework offers an efficient, scalable, and intelligent solution for enhancing intrusion detection and strengthening cybersecurity in modern cloud infrastructures.

8. FUTURE WORK

Future work may focus on implementing the proposed intrusion detection framework in real-time cloud environments such as AWS and Microsoft Azure for continuous network monitoring. Advanced deep learning models including LSTM and Transformer architectures can be integrated to improve detection of sequential and complex attack patterns. The adaptive learning mechanism may also be enhanced using reinforcement learning or online learning techniques for faster model updates. In addition, future research can explore lightweight deployment in edge or fog computing environments and develop web-based dashboards for real-time

visualization, alert generation, and efficient network security management.

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