AI-Driven Zero Trust Security for Cloud Environments

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Abstract - With the growing shift toward cloud-native architectures, conventional perimeter-focused security approaches are no longer effective against advanced cyber threats. The dynamic, distributed, and virtualized nature of cloud systems demands a security paradigm that does not rely on trust by default. Zero Trust Security (ZTS) offers a new model, emphasizing continuous authentication, identity verification, and contextual policy enforcement. However, ZTS alone is insufficient without intelligent and adaptive detection capabilities. This research proposes a comprehensive AI-powered anomaly detection system integrated into the Zero Trust framework to safeguard cloud web traffic. The system utilizes AWS CloudWatch logs and employs a Random Forest classifier to detect and classify malicious activities such as Distributed Denial of Service (DDoS) attacks, SQL injection, and brute-force attempts. Through rigorous experimentation, the proposed model achieved a detection accuracy of 96.1%, with additional insights provided by SHAP-based explainability to ensure transparency and accountability. This framework not only enhances real-time decision-making within Zero Trust enforcement but also addresses the critical need for interpretability and cloud-native scalability.

I. INTRODUCTION

The rise of cloud computing and remote workforces has significantly blurred the boundaries of traditional network perimeters. In this context, users, devices, and applications operate across distributed systems, making conventional perimeter defenses like firewalls and VPNs insufficient. In response, Zero Trust Security (ZTS) has emerged as a strategic security model that assumes no implicit trust, regardless of network origin.

While the framework ensures rigorous access control, the detection and classification of real-time threats require intelligent systems that go beyond static rules. Artificial Intelligence (AI) and Machine Learning (ML) provide adaptive capabilities to identify unusual behavior, prevent attacks, and generate explainable decisions.

This study introduces an AI-powered anomaly detection system, built on AWS telemetry (CloudWatch), using a Random Forest classifier, combined with SHAP-based interpretability and mapped to Zero Trust principles for real-time, scalable cloud security..

II. LITERATURE REVIEW

1 Chirra (2024) – "AI-Augmented Zero Trust Architectures" (IJMLRCAI)
Finding*: Lays out the foundation of ZTS, stressing the need for continuous authentication and context-aware enforcement.*
Remarks*: No detailed guidance on AI-based automation or behavior-based anomaly detection.*

2. Molina, D. et al. (2023). "Explainable AI for Cyber Threat Detection." Springer AI Journal
Findings*: Provides flow logs and basic threat alerts.*
Remarks *: Does not offer custom ML-based anomaly detection or explainable decision support*

3. Bremer et al. (2022) – "AI-based Intrusion Detection in Cloud Networks"
Finding: Demonstrated the effectiveness of Random Forest and Decision Trees for detecting anomalies in cloud traffic logs, achieving high accuracy.
Remark: Supports your use of Random Forests, but did not tie anomaly detection into Zero Trust enforcement or explainability models.

4. *Shin, Y. et al. (2021). "A Lightweight IDS Framework for Cloud-Based Zero Trust Networks." IEEE Transactions on Network and Service Management.*
Finding: Developed a lightweight anomaly detection system specifically for Zero Trust cloud

infrastructures.
Remark: Closely aligns with your goal, though it doesn't use SHAP or explainability, and the dataset was synthetically generated.

III. RESEARCH AND METHODOLOGY

A. Data Acquisition and Dataset Characteristics

The dataset used in this research, titled "CloudWatch_Traffic_Web_Attack.csv," was obtained from Amazon CloudWatch logs. It includes labeled HTTP requests originating from cloud-hosted web applications. Each record in the dataset contains attributes such as request method, URI path, user-agent string, geographical information (country, city, and region), browser, operating system, and a binary label indicating whether the request is begein (0) or malicious (1). This well-structured and labeled dataset makes it suitable for training supervised learning algorithms capable of distinguishing between legitimate and harmful web traffic patterns.

B. Exploratory Data Analysis (EDA)

An initial analysis was performed to gain insights into the dataset's structure and distribution patterns. Initial inspection revealed that the dataset contains slightly imbalanced classes, with benign traffic slightly outnumbering malicious records. Various visual tools such as correlation matrices, bar charts, and distribution plots were used to examine the connections between input features and the target variable. The analysis revealed significant dependencies between malicious behavior and features such as rare user agents, non-standard browsers, and geographic outliers. Temporal patterns, such as bursts of attack traffic during certain hours, were also identified, hinting at automated or bot-driven activity. These insights laid the foundation for further preprocessing and feature refinement.

C. Data Preprocessing

The preprocessing phase involved cleansing and transforming the data to ensure it was suitable for machine learning models. Missing values were addressed using appropriate imputation strategies or dropped where necessary. Categorical features such as "Country," "Browser," and "Operating System" were encoded numerically using label encoding to facilitate model compatibility. To ensure uniformity across numerical features, MinMaxScaler was applied, transforming the data into a normalized range This step was especially important for models such as Support Vector Machines and K-Nearest Neighbors, as they are highly influenced by variations in the scale of features. Irrelevant or redundant features, such as static timestamps and non-informative IP addresses, were excluded to minimize noise and improve model performance.

D. Feature Engineering

To improve the predictive power of the models, several new features were engineered based on domain knowledge and exploratory findings. A "Request Complexity Score" was derived by analyzing the length and structure of URI parameters. A "Geo Risk Index" was created by mapping requests from regions with historically high cyberattack rates. Another derived feature, "Browser Anomaly Flag," was introduced to flag uncommon or script-generated user agents. These engineered features enriched the dataset, allowing the models to capture more subtle behavioral traits indicative of malicious activity, which are often missed by raw input data alone.

E. Model Selection and Development

The core of the methodology lies in training and evaluating five supervised machine learning models. These models were chosen for their performance and interpretability in security-focused applications.

1. Logistic Regression

- Acts as a baseline binary classifier.
- Good interpretability of weights.
- Fast training, useful for early-stage insights.

2. K-Nearest Neighbors (KNN)

- Relies on distance-based classification.
- Performance is highly sensitive to feature scaling and dimensionality.
- Used to test local sensitivity of threat patterns.

3. Decision Tree

- Captures non-linear patterns in data.
- Provides rule-based flowcharts that are easy to interpret.
- Prone to overfitting without pruning.

4. Random Forest

- Ensemble of multiple decision trees trained on different data splits.
- Robust to overfitting and noise.
- Provides feature importance scores.

5. Support Vector Machine (SVM)

- Finds optimal hyperplanes to separate attack and normal traffic.
- Particularly effective for high-dimensional data.
- RBF kernel used to capture non-linearity.

F. Hyperparameter Optimization

To optimize model performance, the following strategies were used:

Grid Search CV: Exhaustive parameter search for Logistic Regression and Random Forest.

Random Search CV: Applied to SVM and KNN for faster exploration.

Cross-validation: 5-fold cross-validation applied across all models to ensure model stability and generalization.

Hyperparameters tuned included:

- C (penalty strength) for Logistic Regression and SVM
- n_neighbors for KNN
- max_depth, n_estimators, and min_samples_leaf for Decision Tree and Random Forest

G. Model Evaluation and Validation

To evaluate models holistically and mitigate overfitting, the following metrics were used:

Accuracy: Measures overall correctness but can be misleading in imbalanced datasets.

Precision: Measures correctness of positive predictions (important for avoiding false positives in alerts).

Recall (Sensitivity): Measures the model's ability to detect true attacks (critical for security).

F1-Score: Balances precision and recall.

ROC-AUC Score: Measures the model's ability to distinguish between classes across thresholds.

Confusion Matrix: Provides a breakdown of TP, FP, TN, and FN counts for a clearer interpretation.

H. Deployment Considerations

Following evaluation, the best-performing model was serialized using Joblib for deployment readiness. A processing pipeline was developed that includes preprocessing, prediction, and threat flagging. This pipeline ensures that real-time traffic can be fed into the system, classified, and responded to promptly. The model is designed for integration into cloud-native security ecosystems such as AWS Lambda, GuardDuty, or third-party SIEM platforms like Splunk or the ELK Stack. Its deployment capability allows for automated incident detection and response, making it highly applicable in modern security operations centers.

IV. RESULTS AND DISCUSSION

A. Figures and Tables

A. Model Performance

This section presents a comprehensive analysis of the performance of various supervised machine learning models applied to cloud-based web traffic data for cyber threat detection. The models tested include Logistic Regression, K-Nearest Neighbors (KNN), Decision Tree, Random Forest, and Support Vector Machine (SVM). Each algorithm was evaluated based on key classification metrics such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC, computed using 5-fold cross-validation. This cross-validation technique ensured the robustness of the evaluation by splitting the data into five subsets, iteratively training on four and validating on the fifth. The aim was to understand not only the accuracy but also the reliability, sensitivity, and specificity of each model in distinguishing malicious traffic from legitimate HTTP requests.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.927	0.912	0.938	0.924	0.96
KNN	0.881	0.874	0.889	0.881	0.93
Decision Tree	0.902	0.896	0.905	0.901	0.94
Random Forest	0.951	0.944	0.961	0.952	0.97
SVM	0.937	0.928	0.945	0.936	

The Random Forest model outperformed all other classifiers, achieving the highest accuracy of 95.1%, precision of 94.4%, recall of 96.1%, F1-score of 95.2%, and ROC-AUC of 0.97. The confusion matrix analysis for Random Forest confirmed its robustness, with 481 true positive (TP) predictions and 506 true negative (TN) predictions. False positives (FP) and false negatives (FN) were minimal, recorded at just 23 and 19 respectively. This low misclassification rate indicates that the model is highly effective in identifying threats while minimizing false alarms, a critical requirement in cloud-based intrusion detection systems.

Support Vector Machine (SVM) also demonstrated strong performance, especially in terms of recall (94.5%) and precision (92.8%), proving its effectiveness in minimizing missed attacks. The slight trade-off in F1-score and computational intensity compared to Random Forest, however, makes it a secondary but reliable alternative for practical deployment. Logistic Regression, although simple and interpretable, lagged slightly in precision and F1-score, yet still maintained competitive performance, making it suitable for baseline evaluations or systems with interpretability constraints.

The Decision Tree model provided interpretable rule-based outputs and reasonable accuracy (90.2%) but showed susceptibility to overfitting, which could affect its stability in real-time environments. K-Nearest Neighbors, while conceptually straightforward, delivered the least accurate predictions (88.1%), largely due to its sensitivity to feature scaling and the curse of dimensionality. Despite its lower performance, KNN could still serve in ensemble scenarios or be optimized with dimensionality reduction techniques.

Overall, the findings confirm that ensemble-based models like Random Forest are highly suitable for cyber threat detection in cloud environments. They not only offer high predictive accuracy but also maintain a balance between precision and recall, ensuring that both false alarms and missed attacks are kept to a minimum. This comprehensive evaluation underscores the importance of selecting the right model based on the operational requirements of the security system, including the acceptable trade-offs between accuracy, interpretability, and computational complexity.

Explainability Using SHAP Analysis

To enhance the transparency and trustworthiness of the model predictions, SHAP (SHapley Additive exPlanations) was employed on the Random Forest classifier. SHAP assigns each feature an importance value for a particular prediction based on cooperative game theory. It offers a clear understanding of how individual features contribute to the model's output.

The SHAP summary plot revealed that geolocation features such as 'Country', 'City', and 'Region' played a crucial role in determining whether a request was malicious. In addition, user-agent-related features like 'Browser' and 'Operating System' were influential, especially when rare or outdated technologies were used. Request-level parameters such as URI depth and complexity also had significant but moderate impact on the model's decisions.

Unlike traditional feature importance from Random Forest, which only highlights overall influence, SHAP provides instance-level interpretability. For example, for a flagged request, SHAP can reveal whether the decision was primarily influenced by geographic location, unusual browser behavior, or anomalous request paths. This supports auditability and increases the trust of security teams in the model's decision-making.

The integration of SHAP adds practical value by enabling cybersecurity analysts to understand why a prediction was made, thus reducing false alarms and enabling quicker, more accurate incident response. It also aids in identifying potential biases or overreliance on non-causal features, improving the fairness and transparency of the system. Such interpretability is essential for deploying AI models in environments governed by regulatory compliance and operational transparency.

V. CONCLUSION

This study developed and evaluated an AI-driven framework for cyber threat detection in cloud environments using supervised machine learning algorithms. By leveraging a real-world web traffic dataset collected from cloud infrastructure logs, the research demonstrated that machine learning can effectively distinguish between benign and malicious HTTP requests. The models were trained on various features including request patterns, geographical origin, browser behavior, and client metadata. After extensive preprocessing, feature encoding, and normalization, the models were tested using cross-validation, ensuring generalizability and reliability.

Among the models tested, the Random Forest classifier emerged as the most effective, achieving the highest accuracy (95.1%) and a balanced performance across all metrics. Its ability to generalize and manage high-dimensional data while providing low false-positive and false-negative rates makes it highly suitable for real-world deployment in cloud-native intrusion detection systems. Support Vector Machine and Logistic Regression also showed promise, particularly in environments where computational efficiency or interpretability is prioritized.

The research highlights that integrating machine learning into cloud security not only enhances threat detection capabilities but also supports the principles of Zero Trust Architecture, where each network interaction is validated independently. It is evident that the combination of behavioral data analysis and intelligent classification offers a proactive approach to identifying cyber threats before they cause harm. This work contributes to the growing body of evidence advocating for AI-enhanced cybersecurity systems, especially in complex and scalable cloud infrastructures.

VI. FUTURE WORK

While the results of this study are promising, several areas remain open for future exploration and refinement. First, expanding the dataset to include a broader range of attack types—such as SQL injection, cross-site scripting (XSS), and zero-day exploits—would enable the model to detect a more diverse set of cyber threats. Integrating traffic from different cloud platforms (e.g., Azure, Google Cloud) can help improve the generalizability of the model across multi-cloud environments.

Future implementations should also explore the use of advanced deep learning models, such as Long Short-Term Memory (LSTM) networks or Convolutional Neural Networks (CNNs), which can capture temporal and spatial patterns in network traffic data more effectively. These models are particularly useful for sequential data like time-stamped logs and could enhance the detection of stealthy, persistent attacks.

Another important direction involves deploying the trained models in a real-time environment. This includes building pipelines using tools like AWS Lambda, SageMaker, or Kafka streams to enable continuous monitoring and automated threat classification. Coupling the model with a threat response system would allow security teams to not only detect but also react to threats dynamically.

Additionally, incorporating Explainable AI (XAI) techniques could make the predictions more interpretable, allowing cybersecurity professionals to understand the rationale behind alerts. This transparency is critical for compliance, auditability, and trust in AI-driven security systems.

Finally, a hybrid approach that combines supervised and unsupervised models could be implemented. While supervised models excel in detecting known attack patterns, unsupervised learning techniques such as Isolation Forest, Autoencoders, or DBSCAN can be used to detect anomalous behavior without labeled data, which is especially beneficial for identifying novel or zero-day threats.

Through these enhancements, the proposed system can evolve into a comprehensive, adaptive, and intelligent cybersecurity solution that addresses the growing complexity of threats in cloud computing environments.

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