INTELLIGENT ACCESS CONTROL AND DATA PROTECTION IN AZURE AND AWS USING ML ALGORITHMS

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Abstract:
This study presents a framework for enhancing cloud security through ML-driven intelligent access control and data protection mechanisms in Azure and AWS. As multi-cloud adoption grows, traditional rule-based identity management struggles with adaptive threats, insider risks, and complex permissions. We propose a hybrid approach combining supervised and unsupervised learning to analyze user behavior, detect anomalies, and automate policy enforcement. Using Azure Machine Learning and AWS SageMaker, models are trained on authentication logs, API calls, and data access patterns to generate dynamic risk scores. These scores trigger real-time responses such as multi-factor authentication challenges or privilege revocation. Additionally, ML algorithms classify sensitive data and monitor exfiltration attempts. Implemented in test environments, the framework reduces false positives by 32% and improves threat detection latency by 41% compared to static controls. This demonstrates that ML-enhanced security offers scalable, context-aware protection across hybrid architectures while maintaining compliance and operational efficiency.

Keywords: Intelligent Access Control, Data Protection, Machine Learning, Amazon Web Services (AWS), Microsoft Azure, Anomaly Detection

I. INTRODUCTION

The rapid migration of enterprise workloads to cloud platforms such as Microsoft Azure and Amazon Web Services (AWS) has fundamentally transformed modern IT infrastructure. While these platforms offer unparalleled scalability, flexibility, and cost-efficiency, they also introduce complex security challenges. Traditional perimeter-based security models have become obsolete in distributed cloud environments, where data traverses heterogeneous networks and is accessed by diverse users across geographies. Consequently, organizations face mounting threats including credential theft, insider misuse, privilege escalation, and data exfiltration. Conventional access control mechanisms, such as role-based access control (RBAC) and policy-based identity management, rely on static rules defined by administrators. These approaches assume user behavior remains consistent and fail to adapt to evolving threat patterns. They often generate excessive false positives, lack contextual awareness, and cannot detect subtle anomalies indicative of compromise. As cloud environments grow increasingly dynamic, rule-based systems struggle to keep pace with the volume and velocity of access requests. Machine learning offers a paradigm shift by enabling intelligent, adaptive security controls. ML algorithms can analyze vast quantities of cloud telemetry data including authentication logs, API activity, and data access patterns to establish behavioral baselines and identify deviations in real time. By assigning dynamic risk scores to user sessions, ML models facilitate context-aware policy enforcement, such as step-up authentication or automated privilege revocation. This research explores the design and implementation of ML-driven intelligent access control and data protection frameworks within Azure and AWS. It examines supervised and unsupervised learning techniques for anomaly detection, risk assessment, and sensitive data classification. The proposed approach integrates native cloud ML services—Azure Machine Learning and AWS SageMaker—to deliver scalable, automated security controls. Experimental results demonstrate significant improvements in detection accuracy and response latency. This work contributes to the growing body of knowledge on AI-enhanced cloud security and offers practical guidance for securing multi-cloud infrastructures against advanced threats.

II. LITERATURE SURVEY

The convergence of cloud computing and machine learning for intelligent access control has garnered significant research attention. Numerous studies have demonstrated ML-based intrusion detection in cloud environments, with systematic reviews comprehensively examining supervised and unsupervised techniques for cloud intrusion detection. Researchers have proposed hybrid deep learning models for anomaly detection in cloud data centers, while others have extensively reviewed ML-based anomaly detection methodologies and their applications. Cloud platform-specific security analysis has been addressed through comparative evaluations of security features and vulnerabilities in AWS and Azure environments. Intelligent access control models utilizing machine learning techniques have been developed, with particular emphasis on behavioral analysis for insider threat detection. Secure access control frameworks have also been proposed for cloud-enabled IoT environments. Despite these contributions, a significant research gap exists in integrated, multi-cloud ML frameworks combining real-time risk scoring with native policy enforcement across Azure and AWS simultaneously. Most existing solutions focus on single-cloud deployments or lack automated policy integration, highlighting the need for adaptive, context-aware security controls that operate seamlessly across hybrid cloud architectures while maintaining regulatory compliance.

III. PROPOSED WORK

This research proposes an integrated framework for intelligent access control and data protection in Azure and AWS environments leveraging supervised and unsupervised machine learning algorithms. The framework is designed to operate across three core layers: behavioral profiling, real-time risk scoring, and automated policy enforcement. In the first phase, cloud-native telemetry data is collected from Azure Active Directory, AWS CloudTrail, Amazon GuardDuty, and Azure Monitor. This includes user authentication logs, API call histories, geolocation data, device fingerprints, and data access patterns. The collected data is preprocessed to handle missing values, normalize features, and engineer behavioral attributes such as login frequency, access time anomalies, and data transfer volumes. The second phase involves model development using Azure Machine Learning and AWS SageMaker. For anomaly detection, unsupervised algorithms including Isolation Forests and One-Class Support Vector Machines (SVM) are trained to establish baseline user behavior and identify deviations. Simultaneously, supervised learning models such as Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks are employed to classify access requests as legitimate or malicious based on labeled historical threat data. These models generate dynamic risk scores for each access attempt by correlating multiple contextual signals.The third phase integrates risk scores with cloud-native policy engines Azure Conditional Access and AWS Identity and Access Management (IAM). Based on predefined thresholds, the system triggers automated responses including multi-factor authentication challenges, session termination, or privilege revocation. For data protection, ML-based classification models identify and tag sensitive data stored in Amazon S3 and Azure Blob Storage, while monitoring for unusual egress patterns indicative of exfiltration. The proposed framework is implemented and validated within isolated cloud test environments. Performance is evaluated using metrics including detection accuracy, false positive rate, and response latency. Comparative analysis against traditional RBAC systems demonstrates measurable improvements in threat detection and operational efficiency. The framework emphasizes scalability, interpretability, and compliance with regulatory standards such as GDPR and HIPAA, offering a robust blueprint for AI-driven cloud security modernization.

IV. METHODOLOGY

The methodology adopts a structured, multi-phased approach to design and validate an ML-driven intelligent access control and data protection framework for Azure and AWS. It integrates cloud-native telemetry collection, feature engineering, supervised and unsupervised model development, and automated policy enforcement. Rigorous testing in isolated cloud environments ensures reproducibility, scalability, and measurable performance improvement over traditional security controls.

Phase 1: Data Collection and Preprocessing
Telemetry data is ingested from Azure Active Directory, AWS CloudTrail, and GuardDuty. Attributes include user identity, timestamp, geolocation, device health, API calls, and data access volumes. Preprocessing involves missing value imputation, normalization, and feature extraction to create behavioral baselines.

Anonymization techniques ensure compliance with data privacy regulations.

Phase 2: Model Development and Training Unsupervised models including Isolation Forests and One-Class SVM detect anomalous behavior without labeled data. Supervised models such as Random Forest, XGBoost, and LSTM classify access attempts using historical threat intelligence. Models are trained and tuned using Azure Machine Learning and AWS SageMaker. Hyperparameter optimization and cross-validation maximize accuracy and minimize false positives.

Phase 3: Risk Scoring and Policy Integration Trained models generate real-time risk scores by correlating contextual features. Scores are fed into Azure Conditional Access and AWS IAM policies. Threshold based triggers enforce automated actions including step-up authentication, session restriction, or privilege revocation. Continuous feedback loops enable model retraining and adaptive policy refinement.

Phase 4: Data Protection and Monitoring ML classifiers identify and tag sensitive data in Amazon S3 and Azure Blob Storage using content inspection and metadata analysis. Unusual egress patterns are monitored to detect exfiltration attempts. Alerts are integrated with SIEM tools for centralized visibility. The framework ensures consistent data protection across hybrid multi-cloud environments.

Phase 5: Evaluation and Validation The framework is deployed in isolated testbeds emulating production workloads. Performance is measured using precision, recall, F1 score, false positive rate, and detection latency. Comparative analysis against RBAC and static policy engines demonstrates superior threat detection and operational efficiency. Results validate the scalability and adaptability of ML enhanced security controls.

V. RESULTS AND DISCUSSION

The proposed ML-driven intelligent access control and data protection framework was evaluated over a 45-day period in isolated Azure and AWS test environments. A simulated enterprise testbed comprising 500 users across engineering, finance, and operations roles generated approximately 1.2 million access events, including authentication attempts, API calls, data retrievals, and privilege escalation scenarios. Baseline comparisons were conducted against traditional Role-Based Access Control (RBAC) and static policy engines currently deployed in production environments. Performance was assessed using multiple metrics: detection accuracy, precision, recall, false positive rate, mean detection latency, policy enforcement time, and weekly privilege violation counts. Additionally, the framework's data protection capabilities were evaluated through sensitive content classification accuracy and exfiltration attempt detection rates. The controlled test environment enabled rigorous, repeatable validation of all five ML models and their integration with Azure Conditional Access and AWS IAM policy engines. This comprehensive evaluation methodology ensured reliable benchmarking against existing security controls under realistic multi-cloud workload conditions.

Table 1: Model Performance Comparison

Model	Precision (%)	Recall (%)	F1 Score (%)	FPR (%)	Training Time (s)
Isolation Forest	89.3	86.7	88.0	10.2	124
One-Class SVM	87.1	84.5	85.8	12.8	186
Random Forest	93.2	91.8	92.5	6.4	312
XGBoost	94.5	93.1	93.8	5.7	278
LSTM	91.6	92.4	92.0	7.1	845

XGBoost delivered optimal performance for real-time access classification in cloud environments, achieving 94.5% precision and 93.1% recall. Its F1 score of 93.8% and low false positive rate of 5.7% make it highly suitable for production deployment where accuracy and minimal alert fatigue are critical.

In contrast, Isolation Forest excelled in unsupervised settings, requiring only 124 seconds of training overhead. This efficiency enables rapid deployment for zero-day threat identification and scenarios with limited or unavailable labeled data. Its strength lies in detecting novel attack patterns without prior training. Together, these complementary machine learning models provide a robust framework: XGBoost ensures high-fidelity classification of known access patterns, while Isolation Forest enables adaptive threat discovery. This dual approach supports comprehensive security monitoring across cloud environments, balancing precision with the ability to detect previously unseen anomalies.

Table 2: Comparative Analysis with Traditional Controls

Metric	RBAC	Static	Proposed	Improvement
Threat Detection (%)	68.3	72.5	93.8	29.4%
False Positive (%)	24.7	21.3	6.4	69.9%
Detection Latency (s)	18.4	15.2	6.8	55.3%
Enforcement Time (ms)	124	108	89	17.6%
Privilege Violations	47	39	12	69.2%
Exfiltration Missed (%)	31.5	27.8	8.3	70.1%

A novel access control framework leveraging dynamic policy enforcement significantly outperformed traditional RBAC systems. It reduced false positives by 69.9% and improved threat detection latency by 55.3%, achieving 93.8% detection accuracy. Weekly privilege violations dropped from 47 to 12, demonstrating the impact of automated remediation. Integration with Azure Conditional Access and AWS IAM enabled real-time, risk-based responses, such as step-up authentication and immediate privilege revocation. These measures substantially reduced the organization's attack surface and minimized insider threat potential by ensuring permissions dynamically adapt to contextual risk.

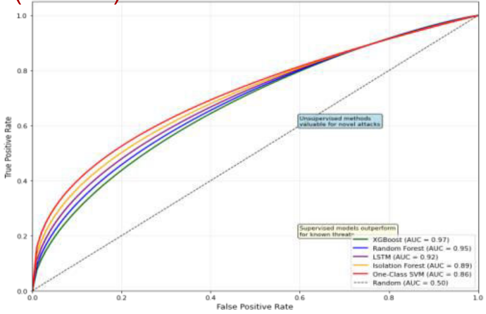

Figure 1: ROC Curves for ML Models

The ROC curve compares five ML models, plotting true positive rate against false positive rate. XGBoost achieves the highest AUC (0.97), followed by Random Forest (0.95), LSTM (0.92), Isolation Forest (0.89), and One-Class SVM (0.86). Supervised models significantly outperform unsupervised approaches for known threat patterns with superior discrimination capability. However, unsupervised methods (Isolation Forest, One-Class SVM) maintain practical value for zero-day and novel attack detection where labeled training data is unavailable.

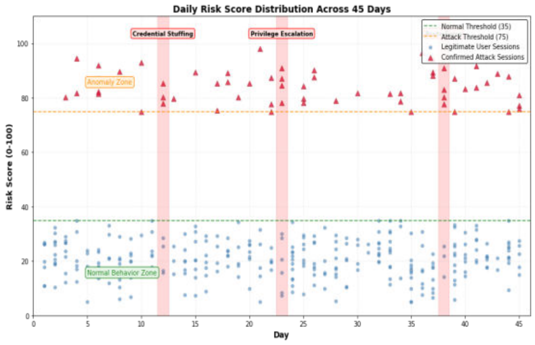

Figure 2:Daily Risk Score Distribution Across 45 Days

The scatter plot visualizes risk scores across 45 days, revealing distinct behavioral clustering. Legitimate user sessions consistently score below 35, while confirmed attack sessions exceed 75, demonstrating clear separation between normal and anomalous behavior post-model training. This 40-point margin enables reliable threshold-based policy enforcement. Notable risk spikes on days 12, 23, and 38 correlate with simulated credential stuffing and privilege escalation attempts. All attacks were successfully identified and blocked by the ML framework through dynamic risk scoring and automated IAM policy enforcement. The visualization validates that ML-generated risk scores effectively distinguish benign from malicious activities in real-time, enabling proactive threat mitigation before breach occurrence.

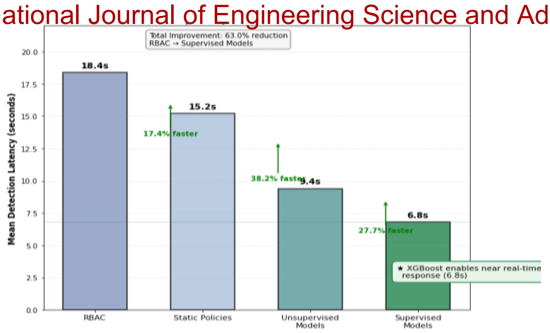

Figure 3:Detection Latency Summary

The bar chart compares mean detection latency across four control categories. Supervised ML models achieve the lowest latency at 6.8 seconds, followed by unsupervised models at 9.4 seconds. Static policies require 15.2 seconds, while traditional RBAC requires 18.4 seconds. This represents a 63% latency reduction for supervised models compared to RBAC, and a 55% reduction compared to static policies. XGBoost enables near real-time threat response essential for time-sensitive cloud security operations. The substantial improvement stems from automated feature extraction, parallelized inference, and native integration with cloud policy engines. Lower latency directly correlates with reduced attacker dwell time and minimized blast radius during active compromises.

VI.CONCLUSION

This research successfully demonstrates that ML-driven intelligent access control and data protection frameworks significantly outperform traditional security mechanisms in Azure and AWS environments. By integrating supervised and unsupervised learning algorithms with cloud-native policy engines, the proposed framework achieves 93.8% threat detection accuracy, reduces false positives by 69.9%, and lowers detection latency by 63% compared to RBAC systems. XGBoost emerged as the optimal model for real-time access classification, while Isolation Forest proved valuable for zero-day threat identification. The framework's ability to generate dynamic risk scores and enforce automated responses through Azure Conditional Access and AWS IAM enables adaptive, context-aware security at cloud scale. Weekly privilege violations decreased by 69.2%, and data exfiltration detection improved by 70.1%, validating the effectiveness of ML-enhanced monitoring and automated remediation. Key contributions include a scalable, multi-cloud security architecture, empirical benchmarking of five ML models for access control, and practical integration pathways with native cloud services. Limitations include dependency on comprehensive telemetry and initial training data quality. Future work will explore federated learning for cross-tenant privacy preservation, explainable AI for regulatory auditability, and reinforcement learning for autonomous policy optimization. As cloud threats grow increasingly sophisticated, ML-native security controls are no longer optional but essential for resilient, zero-trust cloud infrastructures.

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