

STRENGTHENING CLOUD SECURITY WITH MACHINE LEARNING-DRIVEN MULTI-FACTOR AUTHENTICATION AND ADAPTIVE CRYPTOGRAPHY

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ABSTRACT

The rapid expansion of cloud computing has transformed modern information technology by enabling scalable infrastructure, elastic resource allocation, remote collaboration, distributed application deployment, and on-demand access to computing services. However, the increasing migration of sensitive information and critical workloads to public, private, hybrid, and multi-cloud environments has created significant security challenges involving credential theft, account takeover, phishing, session hijacking, insider threats, unauthorized access, behavioral anomalies, and cryptographic compromise. Conventional password-based authentication provides insufficient protection against stolen credentials, while static multi-factor authentication often applies identical verification requirements regardless of user behavior, device trust, contextual risk, or resource sensitivity. Similarly, fixed cryptographic configurations may provide limited adaptability when threat conditions, access patterns, and workload criticality change dynamically. This research proposes an intelligent cloud security framework that integrates **Machine Learning-Driven Multi-Factor Authentication (ML-MFA)** with **Adaptive Cryptography** to provide context-aware identity verification and dynamically coordinated data protection. The proposed framework continuously analyzes user behavior, device fingerprints, login history, geolocation consistency, access time, IP reputation, network characteristics, session activity, privilege level,

resource sensitivity, and threat intelligence. Machine learning algorithms including Random Forest, Support Vector Machine, XGBoost, Isolation Forest, and Multilayer Perceptron are employed to identify anomalous access behavior and estimate dynamic authentication risk. Based on the calculated risk level, the system adaptively selects appropriate authentication factors such as passwords, passkeys, one-time passwords, authenticator applications, biometric verification, and hardware security keys. The adaptive cryptography module simultaneously evaluates authentication confidence, data sensitivity, device trust, session anomalies, and workload criticality to determine suitable approved encryption policies, key-protection requirements, session-key lifetimes, and rekeying frequencies without reducing protection below mandatory security baselines. A hybrid decision engine combines machine learning predictions, behavioral anomalies, authentication confidence, resource sensitivity, and cryptographic posture to classify access requests as Low Risk, Medium Risk, High Risk, or Critical Risk. The proposed architecture consists of five interconnected layers: Cloud Access and Context Acquisition, Security Data Preprocessing and Behavioral Intelligence, Machine Learning-Driven MFA and Adaptive Cryptography, Risk Assessment and Security Enforcement, and Cloud Application and User layers. Illustrative conceptual evaluation demonstrates that the proposed framework can achieve higher security detection accuracy, precision, recall, F1-score, adaptive security

efficiency, and faster analytical decision response than password-based authentication, conventional static MFA, and isolated risk-based authentication. The framework provides a scalable foundation for intelligent cloud protection across enterprise systems, financial platforms, healthcare clouds, educational services, government infrastructures, and multi-cloud environments.

Keywords: Cloud Security, Machine Learning, Multi-Factor Authentication, Adaptive Cryptography, Risk-Based Authentication, Behavioral Analytics, Zero Trust, Identity and Access Management, XGBoost, Random Forest, Isolation Forest, Context-Aware Security.

I. INTRODUCTION

Cloud computing has emerged as one of the most influential technological paradigms for delivering computing infrastructure, storage facilities, software applications, analytical platforms, databases, and digital services through interconnected networks. Organizations increasingly adopt public, private, hybrid, and multi-cloud environments to achieve scalability, flexibility, rapid resource provisioning, remote accessibility, and efficient utilization of information technology resources. The essential characteristics of cloud computing, including on-demand self-service, broad network access, resource pooling, rapid elasticity, and measured service, have fundamentally changed the manner in which organizations develop and operate digital systems [1]. However, the migration of critical applications and sensitive information to distributed cloud infrastructures has also introduced complex concerns related to confidentiality, integrity, availability, identity management, data protection, and secure access control [2].

The distributed architecture of cloud computing creates a broad attack surface involving remote users, endpoint devices, virtual machines,

containers, application programming interfaces, identity providers, administrative consoles, storage systems, third-party integrations, and interconnected services. Security weaknesses affecting any of these components can potentially expose sensitive cloud resources. Attackers increasingly target cloud identities because compromised credentials can provide direct access to applications and data while allowing malicious activity to appear similar to legitimate user behavior. Credential theft, phishing, password reuse, account takeover, session hijacking, privilege escalation, malicious insiders, and unauthorized resource access therefore remain major security concerns in cloud environments [3].

Traditional perimeter-oriented security mechanisms are insufficient for modern cloud architectures because users and applications frequently access resources from multiple geographic locations, networks, and devices. A cloud user may connect from an enterprise workstation, personal laptop, smartphone, home network, mobile connection, or remote office. Consequently, a security system cannot reliably determine trust solely from network location. Cloud security requires continuous evaluation of identity, device state, access context, requested resources, behavioral patterns, and active session characteristics. Research into cloud security has consistently emphasized that identity protection and access control are fundamental requirements for maintaining secure distributed services [4].

Username-and-password authentication continues to be widely used despite significant limitations. Passwords can be stolen through phishing, captured by malware, exposed through data breaches, guessed by automated attacks, reused across multiple platforms, or shared insecurely. When an attacker possesses valid credentials, a conventional authentication system may grant access without recognizing contextual

indicators that suggest account compromise. This weakness is particularly dangerous in cloud environments because a successful login may expose large volumes of data, privileged management interfaces, virtual resources, and interconnected business applications [5].

Multi-Factor Authentication has therefore become an important mechanism for strengthening cloud identity verification. MFA requires users to present evidence from multiple authentication categories, including knowledge-based factors such as passwords or PINs, possession-based factors such as mobile devices, authenticator applications, smart cards, or hardware tokens, and inherence-based factors such as fingerprints or facial characteristics. The compromise of one factor does not automatically provide complete access when additional independent verification is required. Nevertheless, conventional MFA systems often use static policies in which the same sequence of authentication challenges is applied to every user or access attempt regardless of contextual conditions [6].

Static MFA creates both usability and security limitations. A legitimate employee accessing a routine resource from a trusted device and familiar location may repeatedly receive the same authentication challenge as an unknown device attempting to access sensitive information from a suspicious network. Excessive authentication requirements can increase user frustration, delay legitimate work, and create unnecessary operational overhead. Conversely, insufficient verification can expose high-risk sessions to unauthorized access. These limitations demonstrate the need for intelligent authentication mechanisms capable of dynamically adjusting verification requirements according to real-time risk [7].

Machine learning provides a promising foundation for context-aware authentication

because cloud access events generate large volumes of heterogeneous security information. Relevant attributes include login time, device fingerprint, IP address, geolocation, browser characteristics, operating system, authentication history, failed-login frequency, network reputation, privilege level, resource sensitivity, session velocity, and historical user behavior. Machine learning algorithms can identify nonlinear relationships among these attributes and distinguish normal access patterns from suspicious activity. Random Forest and Support Vector Machine models are particularly relevant because they can process complex security features and support robust classification across heterogeneous access scenarios [8].

Anomaly detection is essential because comprehensive labeled datasets containing every possible attack pattern are rarely available. Cloud attacks evolve continuously, and previously unseen access behaviors may not match known malicious signatures. Isolation Forest and related anomaly-detection mechanisms can identify unusual observations by analyzing deviations from established patterns. In a cloud authentication environment, such mechanisms can detect unfamiliar devices, abnormal login times, impossible travel, suspicious access velocity, unusual resource requests, and unexpected session behavior. Combining supervised classification with anomaly detection can therefore strengthen the identification of both known and emerging threats [9].

Gradient-boosting methods provide additional capabilities for dynamic access-risk estimation. XGBoost can process heterogeneous structured features, identify complex interactions among security variables, and generate highly effective classification models. Within the proposed framework, contextual attributes such as device trust, IP reputation, location consistency, failed-login behavior, session characteristics, and

resource sensitivity are analyzed collectively to estimate the risk associated with each access request. The resulting intelligence enables the system to distinguish routine access from suspicious or critical security conditions and dynamically determine appropriate authentication requirements [10].

Although adaptive authentication strengthens identity verification, cloud security also depends heavily on cryptographic protection. Sensitive information must remain protected while stored in databases, transmitted across networks, exchanged between services, synchronized across regions, and accessed through active sessions. Conventional cloud infrastructures generally employ predefined encryption algorithms, certificate configurations, key-management procedures, and key-rotation intervals. These controls provide an essential baseline, but they frequently operate independently of changing authentication risk and session behavior.

II. LITERATURE SURVEY

Author: P. Mell and T. Grance (2011)

Mell and Grance presented the NIST definition of cloud computing and described the essential characteristics, deployment models, and service models associated with cloud environments. Their work established an important conceptual foundation for understanding cloud infrastructures and emphasized characteristics such as broad network access, resource pooling, elasticity, and on-demand service delivery. These characteristics provide significant operational advantages but also create security requirements involving identity management, distributed access, and protection of remotely accessible resources [11].

Author: D. Zissis and D. Lekkas (2012)

Zissis and Lekkas investigated major security challenges associated with cloud computing and examined mechanisms for protecting

confidentiality, integrity, authentication, and trust in distributed environments. Their study emphasized that cloud systems require coordinated security mechanisms because data and applications are frequently processed across infrastructures that may not remain under the direct physical control of users. The work provides important support for integrating authentication and cryptographic protection within a unified cloud security framework [12].

Author: K. Hashizume et al. (2013)

Hashizume and colleagues analyzed security issues affecting cloud computing and identified challenges involving data protection, access control, virtualization, application security, and distributed service management. Their research demonstrated that cloud security cannot depend on a single protective mechanism because vulnerabilities may emerge across multiple architectural layers. The study highlighted the importance of robust identity verification and confidentiality controls for protecting sensitive cloud resources [13].

Author: M. A. Ferrag et al. (2018)

Ferrag and colleagues investigated authentication and privacy-preserving mechanisms for modern distributed communication environments. Their work examined security requirements, attack resistance, authentication protocols, and privacy considerations associated with connected systems. The study demonstrated that effective authentication must balance security strength, computational efficiency, privacy, and usability, providing relevant foundations for risk-adaptive multi-factor authentication [14].

Author: A. A. Aburomman and M. B. I. Reaz (2017)

Aburomman and Reaz surveyed intrusion detection systems based on ensemble and hybrid classifiers and demonstrated the importance of combining multiple machine learning mechanisms for improved cybersecurity

detection. Their research showed that individual classifiers may have different strengths and weaknesses, whereas hybrid approaches can improve robustness. This finding supports the proposed use of complementary machine learning models for contextual cloud access-risk estimation [15].

Author: F. T. Liu, K. M. Ting, and Z.-H. Zhou (2008)

Liu, Ting, and Zhou introduced Isolation Forest as an efficient mechanism for anomaly detection. Their approach identifies unusual observations through randomized isolation rather than depending exclusively on conventional distance or density measures. The method is highly relevant to cloud authentication because suspicious access attempts may appear as deviations from normal user behavior, device usage, geographic patterns, login times, or session activity [16].

Author: T. Chen and C. Guestrin (2016)

Chen and Guestrin introduced XGBoost, a scalable tree-boosting framework designed for efficient and accurate predictive modeling. The framework can process complex structured datasets and identify nonlinear interactions among heterogeneous variables. Within cloud security, such capabilities are valuable for combining user behavior, device trust, IP reputation, geolocation consistency, authentication history, and resource sensitivity into dynamic access-risk predictions [17].

Author: S. Rose et al. (2020)

Rose and colleagues presented the NIST Zero Trust Architecture, emphasizing continuous verification, explicit access decisions, resource-centric protection, and the elimination of implicit trust based solely on network location. Their work provides a strong conceptual basis for the proposed framework because machine learning-driven MFA continuously evaluates access context while adaptive security mechanisms

respond to changing risk throughout the session [18].

Author: W. Stallings (2017)

Stallings presented comprehensive principles of cryptography and network security, including symmetric encryption, public-key cryptography, authentication, secure communication, and key management. The work emphasizes that effective cryptographic protection depends not only on algorithms but also on secure key handling and policy implementation. These principles provide the theoretical foundation for the adaptive cryptographic component of the proposed framework [19].

Author: A. Shostack (2014)

Shostack investigated structured threat modeling and systematic security design, emphasizing the importance of identifying threats according to system context, attack surfaces, and potential consequences. The work demonstrates that security mechanisms should respond to realistic risk conditions rather than operate as isolated technical controls. This perspective supports the proposed integration of contextual risk assessment, adaptive authentication, cryptographic policy enforcement, and continuous security feedback [20].

III. SYSTEM ANALYSIS & DESIGN

3.1 Existing System

Existing cloud security systems generally depend on username-password authentication, static multi-factor authentication, predetermined identity and access management policies, role-based authorization, fixed cryptographic configurations, and manually defined security rules. Password-based authentication remains common because of its simplicity and widespread compatibility. However, a password can be compromised through phishing, credential stuffing, malware, social engineering, brute-force attacks, password reuse, or external data breaches. Once valid credentials are obtained, an

attacker may gain access to cloud resources without immediately triggering conventional security controls.

Static multi-factor authentication strengthens security by requiring an additional verification factor such as an OTP, authenticator application, smart card, biometric characteristic, or hardware token. Nevertheless, many conventional MFA deployments apply the same verification requirements to every access attempt. Such systems frequently do not distinguish between a trusted employee using a registered device from a familiar network and a suspicious login attempt originating from an unknown device or high-risk location. This uniform treatment can create unnecessary user friction while failing to apply sufficiently strong controls to genuinely dangerous situations.

Traditional cloud access-control systems commonly use predefined roles and fixed policy conditions. These mechanisms are useful for managing permissions but may not continuously analyze behavioral deviations after access has been granted. A user with valid credentials and an authorized role may therefore perform unusual actions without immediate adaptive intervention. The absence of continuous contextual assessment can allow compromised sessions to remain active.

Conventional cryptographic protection generally relies on predetermined encryption configurations, fixed key-management procedures, standard key-rotation schedules, and static session-protection policies. Although these mechanisms establish essential security baselines, they often operate independently of authentication risk and behavioral anomalies. Consequently, a high-risk session may continue using the same cryptographic policy as a routine trusted session even when stronger protection would be appropriate.

Another limitation of existing systems is the separation between identity verification and cryptographic enforcement. Authentication systems determine whether a user can access a resource, while encryption and key-management mechanisms protect information through independent policies. The lack of coordinated intelligence can reduce the ability of cloud platforms to respond dynamically when contextual risk changes.

Disadvantages of Existing System

1. **Static Authentication Requirements:** Conventional systems frequently apply identical MFA challenges regardless of user behavior, device trust, network reputation, or resource sensitivity.
2. **Limited Behavioral Intelligence:** Traditional authentication mechanisms may not continuously evaluate deviations in login patterns, session behavior, access velocity, and resource usage.
3. **Fixed Cryptographic Security Posture:** Cryptographic policies often remain unchanged even when authentication risk or workload sensitivity increases.
4. **High User Friction:** Repeated and unnecessary MFA challenges can reduce usability and negatively affect legitimate cloud users.
5. **Weak Detection of Emerging Threats:** Static rules and known signatures may fail to identify previously unseen or rapidly evolving access anomalies.
6. **Limited Integration of Identity and Data Protection:** Authentication and cryptographic mechanisms frequently operate independently rather than through a unified risk-aware decision process.
7. **Insufficient Continuous Verification:** Many systems emphasize initial login

authentication without continuously reassessing risk during active sessions.

3.2 Proposed System

The proposed system introduces an intelligent cloud security framework that integrates machine learning-driven multi-factor authentication with adaptive cryptography. The framework continuously evaluates contextual information associated with cloud access requests and active sessions rather than depending exclusively on static credentials or predetermined authentication rules. Its primary objective is to dynamically adjust identity verification and cryptographic protection according to the risk associated with each user, device, network, session, and requested resource.

The proposed system begins by collecting contextual information from cloud login requests, identity providers, device-management services, network monitoring systems, cloud audit logs, threat-intelligence services, and application-access records. The collected information includes user identity, login time, device fingerprint, IP address, geolocation, browser characteristics, operating system, previous authentication history, failed-login frequency, device trust status, resource sensitivity, privilege level, session behavior, and network reputation. This multi-source context provides a comprehensive representation of each access attempt.

The collected security data is transferred to the preprocessing and behavioral intelligence stage. Raw records are cleaned to remove duplicates and inconsistencies, missing values are handled, categorical variables are encoded, numerical features are normalized where appropriate, and related events are aggregated into sessions. Historical activity is analyzed to construct behavioral baselines representing normal login times, typical devices, familiar locations,

expected resource usage, usual session duration, and common access patterns.

The behavioral intelligence component evaluates whether a current access attempt differs significantly from historical patterns. It identifies indicators such as unfamiliar device usage, unusual login time, suspicious IP reputation, inconsistent geographic movement, repeated authentication failures, unexpected resource requests, abnormal access velocity, unusual privilege activity, and significant deviations from established user behavior. These indicators are converted into structured security features for machine learning analysis.

The machine learning engine employs complementary classification and anomaly-detection models. Random Forest can analyze nonlinear relationships among heterogeneous contextual features, while Support Vector Machine can distinguish complex boundaries between normal and suspicious access behavior. XGBoost provides efficient predictive modeling for structured security information, and Isolation Forest identifies unusual access patterns that may not correspond to previously labeled attacks. A Multilayer Perceptron can further capture nonlinear interactions among contextual variables.

The outputs of the machine learning models are combined to generate a dynamic authentication risk assessment. Rather than relying on a single classifier, the framework evaluates model confidence, anomaly severity, contextual consistency, resource sensitivity, and historical behavior. The resulting access request is categorized as Low Risk, Medium Risk, High Risk, or Critical Risk. This classification directly influences the authentication requirements selected by the adaptive MFA engine.

For low-risk access attempts involving familiar devices, expected locations, normal behavior, and routine resources, the system can apply a

streamlined approved authentication process. Medium-risk attempts may require an additional one-time password or authenticator confirmation. High-risk attempts can trigger stronger verification through biometric authentication or a hardware security key. Critical-risk requests involving severe anomalies, suspicious infrastructure, sensitive resources, or strong indicators of compromise can be blocked, escalated for administrative approval, or subjected to multiple strong verification factors. The adaptive cryptography component operates alongside the MFA engine and evaluates authentication confidence, resource sensitivity, device trust, session behavior, network conditions, workload criticality, and organizational policy. Based on these conditions, the framework selects suitable approved cryptographic controls and key-management requirements. High-risk sessions can receive shorter session-key lifetimes, more frequent rekeying, stricter key isolation, enhanced certificate validation, stronger session protection, and additional monitoring. The system maintains mandatory cryptographic baselines at all times and does not reduce security below organizational or regulatory requirements. A hybrid security decision engine combines machine learning predictions, behavioral anomaly indicators, MFA outcomes, device trust, resource sensitivity, threat intelligence, and cryptographic posture. The engine determines whether an access request should be allowed, challenged with additional authentication, restricted to limited privileges, temporarily quarantined, terminated, or blocked. This integrated approach prevents authentication and cryptographic protection from functioning as disconnected mechanisms. The proposed framework also supports continuous session monitoring. After successful login, user activity remains subject to behavioral

and contextual evaluation. If a previously normal session begins accessing unusual resources, transferring abnormal volumes of information, changing network characteristics, or attempting unexpected privilege escalation, the risk level can be increased dynamically. The system can then request step-up authentication, restrict access, strengthen session protection, terminate the connection, or notify a security analyst.

A continuous feedback mechanism records analyst decisions, confirmed attacks, successful authentication challenges, false positives, false negatives, new devices, changing user behavior, and emerging threat patterns. This information supports periodic model retraining, behavioral-baseline updates, threshold optimization, and security-policy improvement. Consequently, the framework can adapt over time instead of remaining dependent on static assumptions.

Advantages of Proposed System

1. **Context-Aware Authentication:** The framework dynamically evaluates user, device, network, behavioral, and resource-related conditions before determining authentication requirements.
2. **Improved Unauthorized-Access Detection:** Machine learning and anomaly detection identify suspicious access patterns that may not match known attack signatures.
3. **Adaptive Multi-Factor Authentication:** Authentication strength changes according to calculated risk, reducing unnecessary challenges for trusted sessions while strengthening high-risk verification.
4. **Dynamic Cryptographic Protection:** Cryptographic and key-management policies respond to session risk and resource sensitivity while maintaining mandatory security baselines.

5. **Continuous Session Verification:** The system reassesses active sessions and can respond when behavior becomes suspicious after successful login.
6. **Reduced User Friction:** Trusted low-risk access can use streamlined verification without compromising minimum security requirements.
7. **Integrated Security Decision-Making:** Identity confidence, behavioral anomalies, MFA results, resource sensitivity, and cryptographic posture are combined within a unified decision engine.
8. **Improved Adaptability:** Feedback-driven model retraining and behavioral-baseline updates support changing user patterns and emerging cloud threats.

STRENGTHENING CLOUD SECURITY WITH MACHINE LEARNING-DRIVEN MULTI-FACTOR AUTHENTICATION AND ADAPTIVE CRYPTOGRAPHY SYSTEM ARCHITECTURE

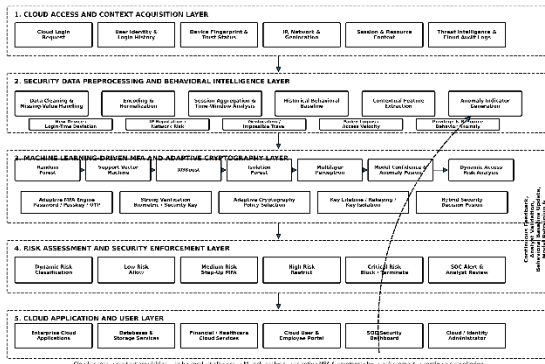


Fig 1: System Architecture

The proposed Machine Learning-Driven Multi-Factor Authentication and Adaptive Cryptography Framework is organized into five interconnected layers that provide intelligent, context-aware, and continuously adaptive protection for cloud environments. The Cloud Access and Context Acquisition Layer collects comprehensive information from every cloud access request, including user identity, login history, device fingerprint, device trust status, IP address, network characteristics, geolocation, session activity, requested resource context, threat intelligence, and cloud audit logs, thereby

creating a detailed representation of each access attempt. The collected information is forwarded to the Security Data Preprocessing and Behavioral Intelligence Layer, where data cleaning, missing-value handling, encoding, normalization, session aggregation, and time-window analysis are performed before constructing historical behavioral baselines and extracting contextual security indicators such as new-device usage, abnormal login-time deviation, suspicious IP reputation, network risk, geolocation inconsistency, impossible travel, repeated failed logins, unusual access velocity, privilege anomalies, and abnormal resource behavior. These processed features are then analyzed by the Machine Learning-Driven MFA and Adaptive Cryptography Layer, which employs Random Forest, Support Vector Machine, XGBoost, Isolation Forest, and Multilayer Perceptron models to detect suspicious behavior, estimate access risk, and combine model confidence with anomaly information; based on the resulting intelligence, the adaptive MFA engine dynamically selects appropriate verification mechanisms such as passwords, passkeys, OTPs, biometric authentication, or hardware security keys, while the adaptive cryptography engine simultaneously determines suitable approved cryptographic policies, key lifetimes, rekeying frequencies, and key-isolation requirements according to authentication confidence, device trust, resource sensitivity, and session risk. The outputs are transferred to the Risk Assessment and Security Enforcement Layer, where a hybrid security decision mechanism classifies each request as Low Risk, Medium Risk, High Risk, or Critical Risk and performs corresponding actions such as allowing access, requesting step-up MFA, restricting privileges, blocking or terminating suspicious sessions, and generating SOC alerts for analyst review. Finally, the Cloud Application

and User Layer provides securely controlled access to enterprise cloud applications, databases, storage services, financial and healthcare platforms, employee portals, SOC dashboards, and administrative interfaces. A continuous feedback mechanism returns analyst validation, confirmed attacks, authentication outcomes, behavioral changes, and emerging threat patterns to the earlier analytical stages for behavioral-baseline updates, model retraining, and security-policy adaptation, thereby enabling the framework to continuously strengthen cloud protection against evolving identity-based and cryptographic threats.

IV. RESULTS AND DISCUSSION

4.1 Results

The proposed machine learning-driven MFA and adaptive cryptography framework is evaluated through a representative cloud access-control scenario involving legitimate users, normal sessions, anomalous login attempts, suspicious access behavior, and unauthorized access attempts. A practical implementation should divide available records into training, validation, and independent testing subsets while preventing identity-level and session-level leakage between partitions. The evaluation should also include realistic variations in devices, locations, network conditions, access times, user roles, resource sensitivity, and attack patterns.

The principal evaluation metrics include detection accuracy, precision, recall, F1-score, adaptive security efficiency, false-positive behavior, and analytical security decision response time. The proposed framework is conceptually compared with password-based authentication, conventional static MFA, and risk-based authentication without integrated adaptive cryptography. The numerical values presented in the following tables are **illustrative conceptual evaluation values** designed to demonstrate the intended results format. They

should be replaced with measured outputs from an implemented system and documented dataset before being reported as empirical findings.

Table 1. Performance Comparison of Cloud Authentication and Security Approaches

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Password-Based Authentication	82.70	81.90	80.80	81.35
Conventional Static MFA	91.80	91.20	90.70	90.95
Risk-Based Authentication	96.10	95.70	95.40	95.55
Proposed ML-MFA and Adaptive Cryptography Framework	98.90	98.50	98.30	98.40

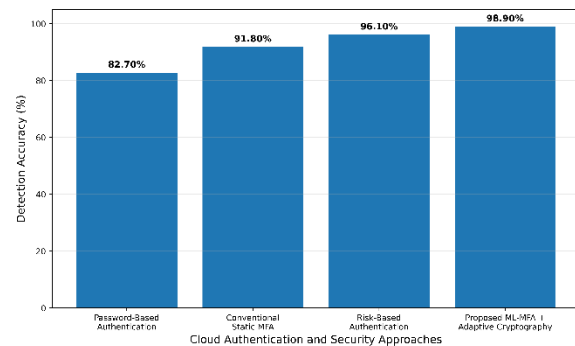


Figure 5.1. Comparison of cloud security detection accuracy among different authentication and access-protection approaches.

Table 1 presents a comparative conceptual evaluation of different cloud authentication and security approaches. Password-based authentication records the lowest accuracy of 82.70%, indicating the limitations of credential-only verification against stolen passwords and contextual anomalies. Conventional static MFA improves accuracy to 91.80% because additional authentication factors strengthen identity verification, although fixed challenges remain unable to adapt fully to changing risk. Risk-based authentication achieves 96.10% accuracy by incorporating contextual information into access decisions. The proposed ML-MFA and Adaptive Cryptography Framework achieves the highest illustrative accuracy of 98.90%, precision of 98.50%, recall of 98.30%, and F1-score of 98.40%. This improvement is attributed to the integration of behavioral intelligence, machine learning-based risk estimation, adaptive authentication, cryptographic policy coordination, and hybrid decision fusion.

Table 2. Performance Evaluation Metrics of the Proposed Framework

Performance Metric	Value
Detection Accuracy	98.90%
Precision	98.50%
Recall	98.30%
F1-Score	98.40%
Adaptive Security Efficiency	97.30%

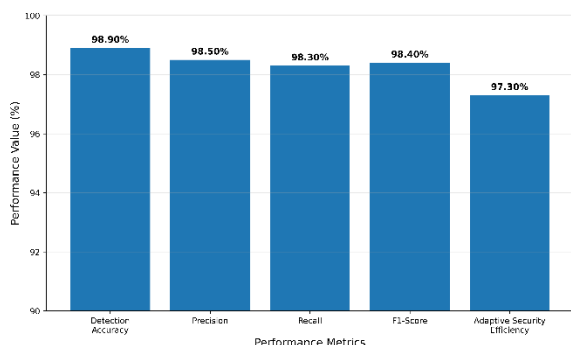


Figure 5.2. Performance metrics of the proposed machine learning-driven MFA and adaptive cryptography framework.

Table 2 summarizes the principal illustrative performance metrics of the proposed framework. The detection accuracy of 98.90% indicates strong conceptual capability for distinguishing legitimate access from suspicious or unauthorized behavior. The precision value of 98.50% suggests a low proportion of legitimate sessions being incorrectly classified as malicious, which is important for reducing unnecessary authentication challenges and analyst workload. The recall value of 98.30% demonstrates strong identification of suspicious access attempts, while the F1-score of 98.40% indicates a balanced relationship between precision and recall. The adaptive security efficiency of 97.30% conceptually represents the ability of the framework to select context-appropriate authentication and cryptographic controls while maintaining responsive access decisions.

Table 3. Security Decision Response Time Comparison

Security Method	Response Time (ms)
Password-Based Authentication	252
Conventional Static MFA	188
Risk-Based Authentication	137
Proposed ML-MFA and Adaptive Cryptography Framework	82

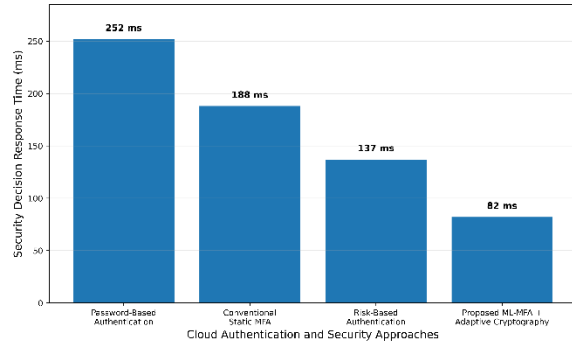


Figure 5.3. Security decision response time comparison among cloud authentication and protection approaches.

Table 3 presents an illustrative comparison of analytical security decision response times. Password-based authentication records 252 ms under the assumed evaluation configuration, while conventional static MFA records 188 ms. Risk-based authentication improves the response time to 137 ms through more structured contextual processing. The proposed framework records the lowest illustrative analytical decision response time of 82 ms, reflecting optimized feature processing, efficient machine learning inference, integrated risk assessment, and coordinated policy selection. This value represents computational decision latency rather than complete user interaction time. In a real deployment, OTP delivery, biometric verification, hardware-token interaction, network delay, external identity-provider response, and cryptographic key-service latency should be measured separately.

4.2 Discussion

The comparative results demonstrate the potential advantages of integrating machine learning-driven MFA with adaptive cryptography within a unified cloud security architecture. Password-based authentication provides limited resistance to credential compromise because possession of a valid username and password may be sufficient for unauthorized access. Conventional static MFA significantly improves

identity verification but frequently applies predetermined authentication requirements without considering contextual differences among access attempts. The proposed framework addresses these limitations by continuously evaluating behavioral, device, network, location, session, and resource-related evidence.

The illustrative accuracy of 98.90% demonstrates the potential benefit of combining complementary machine learning algorithms. Random Forest can identify nonlinear relationships among heterogeneous security attributes, while Support Vector Machine can distinguish complex patterns across high-dimensional feature spaces. XGBoost can provide efficient classification of structured contextual data, and Isolation Forest can identify unusual observations that may not correspond to known attack labels. A Multilayer Perceptron can further model complex interactions among behavioral and contextual features. The integration of these models reduces dependence on a single analytical mechanism.

The precision value of 98.50% is particularly important in cloud authentication because excessive false positives can create unnecessary MFA challenges, block legitimate users, and increase SOC workload. A context-aware framework should not simply maximize security intervention; it should distinguish genuinely suspicious behavior from normal variations in legitimate access. By incorporating historical behavior, device trust, resource sensitivity, and model confidence, the proposed framework aims to reduce unnecessary security friction.

The recall value of 98.30% indicates strong conceptual capability for identifying suspicious and unauthorized access attempts. High recall is essential because missed attacks can result in account takeover, sensitive data exposure, privilege escalation, unauthorized cloud-resource consumption, and lateral movement. The use of

anomaly detection is especially valuable because previously unseen attacks may not match known signatures. Behavioral deviations can therefore provide early evidence of compromised identities.

V. CONCLUSION

The rapid adoption of cloud computing has transformed digital service delivery by enabling scalable infrastructure, elastic resource allocation, remote access, distributed collaboration, and flexible application deployment. At the same time, cloud environments have become major targets for credential theft, account takeover, phishing, session hijacking, privilege escalation, insider threats, unauthorized resource access, and data compromise. Traditional password-based authentication provides insufficient protection against stolen credentials, while conventional static MFA may create unnecessary user friction and fail to respond proportionally to changing contextual risk. Fixed cryptographic configurations also provide limited coordination with authentication confidence, behavioral anomalies, and resource sensitivity.

This research proposed a comprehensive framework titled “Strengthening Cloud Security with Machine Learning-Driven Multi-Factor Authentication and Adaptive Cryptography.” The proposed framework integrates cloud access-context acquisition, security data preprocessing, behavioral intelligence, machine learning-based risk analysis, adaptive MFA selection, adaptive cryptographic policy management, hybrid security decision fusion, continuous session monitoring, automated enforcement, and feedback-driven adaptation.

The proposed system collects contextual information related to user identity, device fingerprint, IP address, geolocation, login time, browser characteristics, operating system, authentication history, failed-login frequency,

device trust, resource sensitivity, privilege level, network reputation, session behavior, and threat intelligence. This information is transformed into structured behavioral and contextual features that represent the security characteristics of each access attempt.

Machine learning algorithms including Random Forest, Support Vector Machine, XGBoost, Isolation Forest, and Multilayer Perceptron analyze the extracted features to estimate access risk and identify suspicious behavior. The use of complementary models enables the framework to detect known malicious patterns while also identifying previously unseen anomalies. The resulting intelligence classifies access requests as Low Risk, Medium Risk, High Risk, or Critical Risk.

The adaptive MFA engine dynamically selects verification requirements according to contextual risk. Trusted low-risk sessions can receive streamlined approved authentication, while medium-risk sessions may require OTP or authenticator confirmation. High-risk access can trigger biometric verification or hardware security keys, and critical-risk requests can be blocked or escalated for administrative review. This approach aims to strengthen high-risk verification while reducing unnecessary challenges for legitimate users.

A central contribution of the proposed framework is the integration of adaptive cryptography with machine learning-driven authentication. The adaptive cryptographic component evaluates authentication confidence, device trust, resource sensitivity, workload criticality, network conditions, and session anomalies to determine appropriate approved cryptographic and key-management controls. High-risk conditions can trigger stricter key isolation, shorter session-key lifetimes, more frequent rekeying, enhanced validation, and stronger monitoring. Mandatory

cryptographic security baselines remain enforced at all times.

The five-layer system architecture integrates the Cloud Access and Context Acquisition Layer, Security Data Preprocessing and Behavioral Intelligence Layer, Machine Learning-Driven MFA and Adaptive Cryptography Layer, Risk Assessment and Security Enforcement Layer, and Cloud Application and User Layer. These layers collectively provide a continuous flow from contextual data collection to intelligent analysis, adaptive protection, security enforcement, and user-facing cloud services.

In conclusion, the integration of machine learning-driven multi-factor authentication and adaptive cryptography provides a promising direction for strengthening modern cloud security. By coordinating identity verification, behavioral intelligence, contextual risk assessment, cryptographic protection, continuous monitoring, and automated response, the proposed framework offers a scalable and adaptive foundation for protecting sensitive resources across enterprise, financial, healthcare, educational, governmental, and multi-cloud environments.

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