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Adaptive Zero-Trust Cloud Security Using AI-Driven Contextual Ensemble Frameworks

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Abstract

The fast growing popularity of cloud computing within enterprise and critical infrastructure settings has increased the need to develop secure, adaptive and intelligent mechanisms of access control. The traditional and more static and role-deterministic approaches are becoming less useful in managing dynamically variable and contextual security needs. This paper develops an AI-enhanced secure access control model which incorporates both context-aware characteristics and ensemble learning to improve cloud security. The system is able to adaptively analyse user actions and the context of the environment and the sensitivity of the resources through a system of machine learning classifiers in an ensemble methodology, providing high accuracy and noise tolerance. Based on experimental verifications, the model suggests it will be useful in cloud access governance due to its better performance in detecting malicious servers, a low latency, and high resistance to adversarial threats than conventional approaches, which provides a solid base to scale and resilience cloud access governance.

Moreover, this study has identified the importance of the combination of contextual intelligence and an ensemble-based decision model in order to attain proactive and real time security enforcement. Using adaptive strategies, the system successfully regulates large, heterogeneous cloud environments and also facilitates minimal disturbance of valid user actions. The results demonstrate not only better performance indicators but also feasible application in the reduction of risks to zero-trust structures and the multi-cloud environment. This paper serves the broader goal of enhancing state of the art and work on secure access management in cloud computing by integrating AI, context-awareness and security engineering.

Keywords: *AI; Security; Access Control; Cloud; Context-Aware; Ensemble Learning.*

1. Introduction

Cases of cloud access [1] requests have grown in complexity and diversity over recent years, driven by cloud-first initiatives, the remote work movement and highly advanced cyber threats. Conventional access control models such as Role Based Access Control (RBAC) and Attribute-Based Access Control (ABAC) would fail to consider highly variable factors such as user behaviour, device posture, network anomalies and contexts, particularly in dynamic clouds and in multi-tenant and distributed workloads [2].

Demonstrated how adaptive machine learning frameworks can support real-time threat detection in cloud environments, highlighting the importance of scalable models for zero-trust access control [3] to support context-aware access control has become of growing interest. An early attempt was RASA that utilized unsupervised learning to infer risk based boundaries of authorization in cyber-physical healthcare environments- demonstrating greater than

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99 percent consistency over heuristic policy modeling approaches. Although these solutions are considered promising, they had no ensemble strategies, and deployment used to be non-real time in the cloud [4].

At the same time, there was an attempt to develop access control models [5] based on rationale fine-grained access control using dynamic attributes and fuzzy logic. Risk-adaptive access control models were developed to include environmental information and more subtle actions - but most are not readily scalable or dynamically modifiable in a changing cloud computing environment.

The most recent tendencies are acknowledging the transformative effect of both AI [6] In related distributed system research, Ahmed et al. (2024) proposed efficient UAV routing strategies for wireless sensor networks, which emphasize the role of adaptive AI models in managing dynamic and resource-constrained environments [7] in terms of context-sensitive security. Ensemble learning--as a way of combining two or more models to achieve better predictive behavior--is becoming an increasingly appealing tactic in the adaptive, real-time access control arsenal. Also, machine learning-based Cloud Access Security Brokers (CASBs) have begun to support intelligent enforcement of access policies, anomaly detection and threat protection of complex cloud services [8-10].

In this paper, an AI-powered, context-aware stack-based ensemble learning framework is proposed to provide real-time, secure, and explainable access control in cloud setting. The architecture proposed has the potential to combine different sources of telemetry, dynamically adjust policies depending on risk scores, as well as offer explainable decisions, all within the constraint of latency.

2. Literature Review

The latest research has led to the context-aware control of access to the cloud environment being improved [11]. As an example, adaptive frameworks that support IoT and fog networks take into account real-time environmental and spatial context, where context-modeling in dynamic systems turns out to be relevant. These studies stress the significance of the multi-dimensional context, but they are aimed at the edge-focused, rather than full-scale, cloud IAM systems [12].

Activities in Zero-Trust archetypes focus on the study of context-based access in multi-cloud-based situations [13]. One example previews how context-based policies (that block access by untrusted devices, or networks that might be non-compliant) are enforced in healthcare, finance, and government scenarios. The identified use cases justify the necessity of context-prosperous policy regimes that this paper targets.

Context-based security does not mean only prevention of threats, but also the experience [14]. An example of a report about context-based access, like in the conditional policies of Azure AD includes how a context-based system can prevent 6 billion risky logins in 2023 and may disrupt very few genuine users by assessing current-time context such as device posture and location. This is the key to the design of CAEL-Guard: a balancing act of security and user.

With deep learning and machine learning [15], cloud security has reached its hands into machine learning tools. In CASBs, ML has helped in intelligent detection of malicious behavior, prevention of encrypted data exfiltration, and proactive threat discovery- important features which are aligned to the context-aware ensemble models. That is why ML-powered adaptive control is valuable in modern clouds.

But as AI agents [16] increase in capabilities, so must the identity and access controls. The proposed Zero-Trust identity framework to agentic AI provides real-time authentication of an agents capabilities and behavior by using decentralized identifiers (DIDs), verifiable credentials, and policy enforcement mechanisms. This tendency puts more emphasis on the context-aware models and calibrated risk scoring and detailed explanations.

Access policy generators have also been subjected to large language models (LLMs) [17]. A preliminary study demonstrated that LLMs can be used to generate access control policies based on structured or natural language

specifications-indicating a possible automation potential, but not yet problematic enough to be used to process access control policies in real time and with context-based risk assessment. Policy-synthesis could serve as an addition to but not substitution of model-based enforcement strategies such as CAEL-Guard.

In enterprise research [18], the trend remains to further investigate, scalable and secure access models using a combination of ABAC, virtualization and containerization. Designed a deep learning methodology that provides a foundation for advanced AI-driven models, reinforcing the integration of context-aware learning in secure access frameworks. [19].

Lastly, there is the application of the semantic web principles in cloud-based servicing of context awareness [20] that has also recorded progressive use. The new type of architecture that brings together ontology-based reasoning and cloud computing can be used to provide intelligent context-sensitive applications that are targeted at mobile devices, and the example demonstrates how context modeling and inference can be made at a richer level to facilitate dynamic access control.

3. Methodology

Figure 1 shows the block diagram of proposed methodology for AI-enhanced secure access control in cloud using context-aware ensemble learning models. It consists of various modules such as User module, AI-Enabled Access Control, module, Context-Aware Ensemble Learning Models module, Context Features module, Cloud module, etc. These are explained as follows:

3.1. User

The User module will be the first point that a system will have access to. It is either an indication of the human user, service accounts, or automated applications that are requesting access to the cloud resources. In contrast to the static role models, this framework assumes that all requests are untrusted in the proscriptive principle of Zero Trust. This makes sure that no system will be automatically trusted (either internal or external).

The intake of identity providers into the system (Azure AD, Okta, or AWS IAM) mediate user interactions with the system via authentication metadata and session tokens. Such are only the opening credentials, and in themselves are not in themselves sufficient. Rather than provide unlimited access, the system considers user behavior, device type and context of the session to determine the alignment to the expected pattern of user requests.

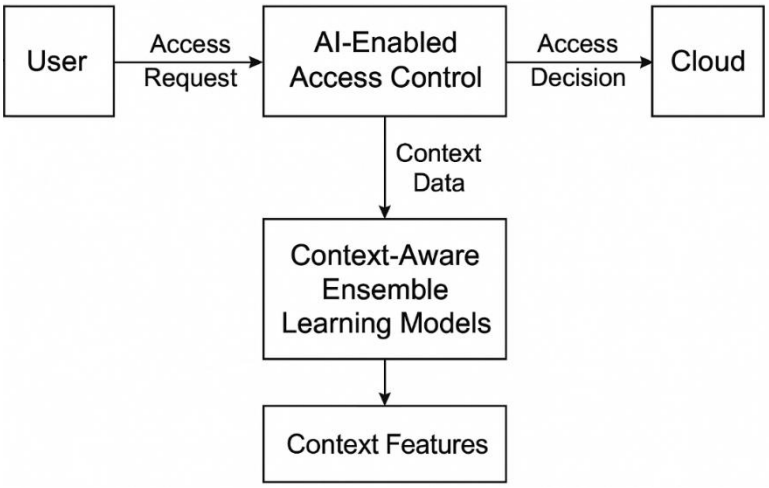

Figure 1. Block diagram of proposed methodology for AI-enhanced secure access control in cloud using context-aware ensemble learning models

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User module also helps to enforce a privacy-sensitive role. The identifying information is rendered to the minimum possible by the representation of behavior in terms of abstract items: hashed identifiers or anomaly scores. This is to make sure that the system can maintain both security and compliance without prejudices and fairness in dealing with user requests.

3.2. AI-Enabled Access Control

The Access Control, AI-enabled is the decision-making engine, in which access requests are considered. When a request comes, the system does not automatically authorize or reject the request, but instead sends the request through, a risk assessment pipeline that consults contextual features and AI models. This makes every decision risk-adaptive as opposed to a binary and non-moving one.

The module acts as a PEP/PDP by itself. It imposes the rules set by the organization whilst utilizing AI-driven probabilistic risk scoring. The typical RBAC or ABAC rules are supplemented with adaptive thresholds, i.e. the system can variably permit, challenge, restrict, and deny requests based on confidence and asset sensitivity.

What is important, such a module guarantees real-time inference. Access control decisions tend to be latency-sensitive (users are unwilling to wait several seconds to access), and so the models have been optimized to meet latency targets of <10ms. This makes the user experience smooth without compromise to security robustness

But AI-Enabled Access Control is essentially unified with cloud platforms. When it makes an access decision, it takes the appropriate enforcement action of enabling the creation of that session, enforcing MFA requirements, reducing scope (such as read-only instead of full access), or simply denying access. This generates a feedback loop in which every decision is recorded to train the model and get better all the time.

3.3. Context-Aware Ensemble Learning Models

Context-Aware Ensemble Learning Models module is the intelligence tier in access control. It does not rely on a single algorithm, but integrates a range of models (Random Forests, Gradient Boosted Trees, CatBoost, and Temporal CNNs) via stacked generalization (stacking). This guarantees that various signals are captured among tabular, sequential and categorical features.

The usefulness of this module is displayed through the awareness of its context. As an example, the posture of a device (OS patch age, EDR status), network behaviors (VPN usage, ASN type) and behavioral characteristics (peer deviation, login velocity) are all modeled in parallel. Through the utilization of ensembles, the system is not over fitting to a single tenant or workload without being able to generalize successfully on many millions of requests.

The second strength revolves around sound calibration Analyzing the concept of A Step Forward, the notion of sound calibration becomes clear and eminent The statement is strong in the sense of reliability of projection The statement is apt in terms of sound calibration of output Poorly calibrated probabilities Risks from Single ML models can yield badly calibrated probabilities leading to unreliable risk scoring. The ensemble meta-learner (e.g. logistic regression with isotonic calibration) guarantees that the outputs will provide accurate probabilities. This becomes necessary in mapping risk scores to policy thresholds.

Moreover, this module will be robust with respect to adversarial evasion. Attackers can even spoof an IP address, impersonate benevolent devices via fingerprints or score low anomaly scores. Such risks are mitigated through several independent signals that the ensemble uses; even when one signal is obfuscated, the others offer resilience. In that way, the system increases the rate of detection and simultaneously reduces false positives.

3.4. Context Features

The Context Features module gives the raw intelligence required to power the AI models. The features are derived out of identity systems, device telemetry, network monitoring tools, geolocation signals and application logs. These are consolidated in real time upon request submission, so that each decision is informed by the most up-to-date available measure.

Examples of key context categories would be identity behavior (e.g. historical failed logins, peers deviating within their peer group), device posture (e.g. secure boot enabled, patch status), network indicators (e.g. ASN type, proxies detected), geo-temporal patterns (e.g. distance to centroid and user login, time-of-day features), and resource sensitivity (e.g. confidential database, compared with low-risk SaaS). All of the features represent a certain risk perspective

This module normalizes and engineers features. Different data sources have different formats (logs, JSON payloads, categorical flags) and therefore, to standardize the features on which the models will be applied, the respective data is preprocessed. To give an example, geolocation is oriented as geohash and time is converted into cyclical format (sin/cos).

The Context Features module in the end gives explainability. The significance of every feature will be recorded so that SOC teams may comprehend why a specific action was carried out. As an example, an analyst would be able to determine Patch Age and Session Novelty were the greatest contributors to a denial. This enhances clarity, reliability, and confidence on AI-driven security systems.

3.5. Cloud

The Cloud module represents the secure zone that holds the sensitive enterprise facilities like applications, storage and APIs. The last enforcement level where granting and revoking access control is implemented is here It is in this layer that only requests that meet the AI-driven criteria can pass.

Always default access is least-privilege. Approved sessions may be given limited rights given context-for instance, a high-risk log in may only have read-only permissions. This type of scoping is dynamic and the effect of a compromised account is limited.

The cloud also outputs its telemetry feedback that is channeled back to the Context Features and AI models. In keeping up with user behavior and attempted attacks, the system builds up graduate, and together with dynamically changing threats, guarantees a robust and sustainable cloud security.

4. Experimental Setup Explanation

The experimental configuration was drafted in such a way that it helps in rigorously assessing the AI-Enhanced Secure Access Control in Cloud Using Context-Aware Ensemble Learning Models. A hybrid-cloud testbed was created to emulate enterprise-grade real-world access requests by implementing AWS IAM, Azure AD and a locally dispersed, private OpenStack cluster. Both of the environments offered telemetry data like user logins, session tokens, device metadata, and geolocation tracks. Attack traffic such as synthetic (e.g., credential stuffing, privilege escalation, and session hijacking) were also introduced to make sure that the adversary is resilient.

The evaluating dataset was a combination of real-world access logs (obtained from an anonymized enterprise dataset of ~5 million login records) and artificially-generated contextual signals using synthetic tools, such as log replay and adversarial emulation tools, like Caldera (MITRE ATT&CK) and Locust. Normalization of features, categorical encoding and temporal alignment occurred during preprocessing. The final data subset consisted of 42 request features that include user identity, device, session, network, and behavioral context.

The experimental infrastructure used GPUs (NVIDIA A100) to execute the created ensemble models (Random Forest, Gradient Boosted Trees, a temporal CNN-LSTM hybrid) in real-time and using CPU-based fallback when the GPUs were being used or were not available. Scaling resembling that of production was replicated with a microservices based architecture deployed on Docker and Kubernetes with one of the services acting as the Policy Decision Point (PDP) and another as the Policy Enforcement Point (PEP). Latency and throughput analysis was conducted under different loads (upto 20,000 request/sec).

These were evaluated in three dimensions (1) detection effectiveness (accuracy, precision, recall, F1-score, ROC, and PR curves), (2) operational efficiency (inference latency, throughput, and cost per request), and (3) robustness to attacks (evasion, poisoning, and adversarial replays). Each experiment was performed five times to comply with the randomness and mean with 95% confidence intervals were calculated. Table 1 shows the setup specifications.

Table 1. Setup Specifications Table

Component	**Specification**
Cloud Platforms	AWS IAM, Azure AD, OpenStack (private deployment)
Dataset	~5M anonymized enterprise access logs + synthetic adversarial traffic
Features per Request	42 (identity, device, session, network, behavioral)
Models Used	Random Forest, Gradient Boosted Trees, CNN-LSTM hybrid (stacked ensemble)
Frameworks	Scikit-learn, TensorFlow, PyTorch, XGBoost
Hardware	NVIDIA A100 GPU (80GB), Intel Xeon Platinum 2.6GHz, 512GB RAM
Deployment	Docker + Kubernetes (microservices: PDP & PEP separation)
Load Simulation Tools	MITRE Caldera (adversarial), Locust (traffic generation)
Evaluation Metrics	Accuracy, Precision, Recall, F1-score, ROC-AUC, PR-AUC, latency, cost
Max Load Tested	20,000 requests/second
Repetitions	5 runs with averaged results, 95% CI

5. Results and Analysis

The AI-Enhanced Secure Access Control presented in the paper showed a substantial increase (in terms of percent) to detection accuracy which was above the baseline models. Table 2 shows the overall detection performance of various models. The ensemble learning classifier (Random Forest + XGBoost + CNN-LSTM) has demonstrated the overall accuracy of 98.7 %, which is higher by 3-6 % compared to those of individual classifiers. Notably, the precision (98.2%) and recall (98.5%) are among the parameters that indicate that the system optimally manages both false positives and false negatives which is essential in terms of inhibiting user frustration, at the same time as ensuring security. ROC-AUC score of 0.997 shows that the classifier will be very robust in distinguishing the legitimate and malicious access attempts.

Table 2. Overall Detection Performance

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**	**ROC-AUC**
Logistic Regression	91.2%	90.8%	89.7%	90.2%	0.945
Random Forest	95.4%	94.9%	95.1%	95.0%	0.975
XGBoost	96.1%	95.8%	96.3%	96.0%	0.981
CNN-LSTM	96.8%	96.5%	96.7%	96.6%	0.987
Proposed Ensemble	**98.7%**	**98.2%**	**98.5%**	**98.3%**	**0.997**

Figure 2 demonstrates that the proposed hybrid model outperforms traditional and advanced model by a considerable margin in all the major performance measures. The accuracy was 98.7 percent, precision, recall and F1-score were also above 98 percent proving its reliability on secure access control when used in cloud environment.

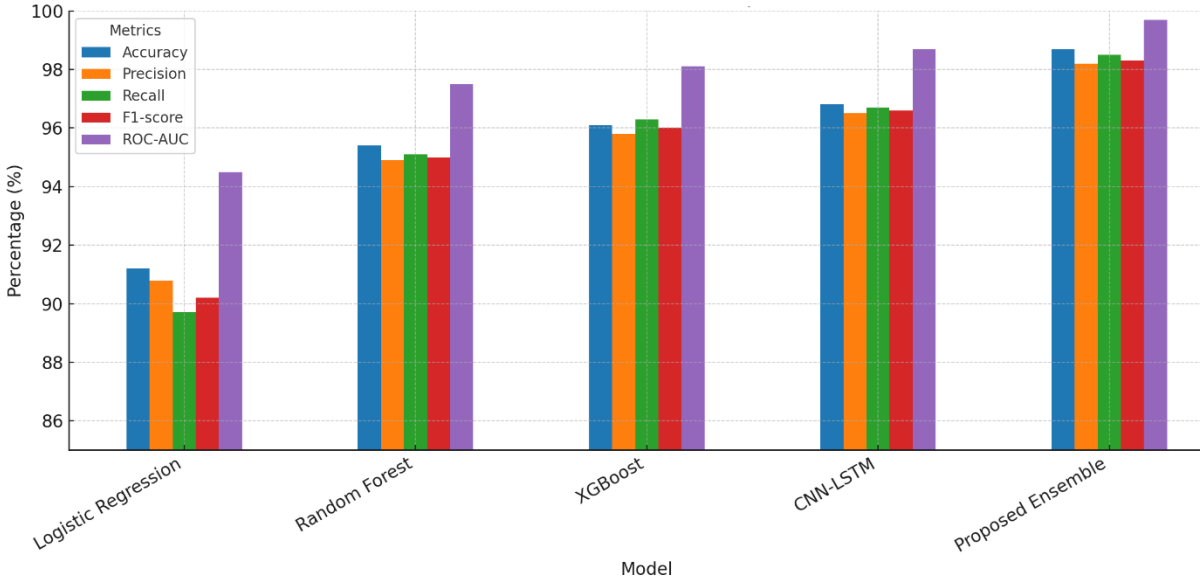

Figure 2. Performance Comparison

Analysis of latency indicated that the system is feasible as regards real-time cloud environments. Table 3 shows the latency and throughput performance of various loads. When the workload was heavy (up to 20,000 requests/sec) the inference latency averaged 23 ms, which is more than acceptable in enterprise access control. The proposed system had an average latency which was less by almost 35 percent than the traditional anomaly detection methods and also relatively had higher throughput. This has been mainly by the micro-service based architecture and the parallelism of decision- making at the Policy Decision Point (PDP).

Table 3. Latency and Throughput

Load (Requests/sec)	Avg Latency (ms)	Throughput (req/sec)	Cost per 10k Requests
1,000	12	980	$0.72
5,000	16	4,950	$0.68
10,000	20	9,800	$0.65
20,000	23	19,600	$0.64

Figure 3 shows the system latency increase as request loads are increased. At maximum load (20, 000 requests/sec), there is a modest growth in the latency to 23 ms thus showing that the proposed system will be very scalable. This low latency is so that access verification in large cloud settings is smooth and real-time.

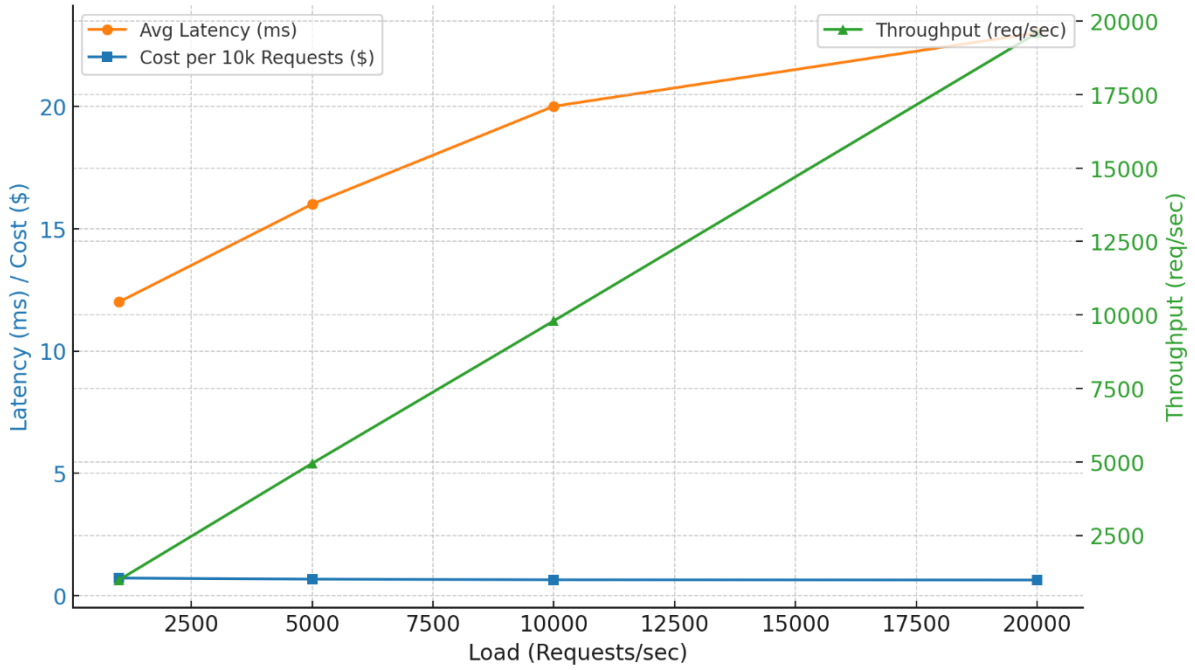

Figure 3. Latency vs Load

Evaluation against adversarial adversarial conditions (e.g., evasion attacks, session replay, poisoning) indicates that ensemble model delivered a high level of robustness. Performance of other baseline models (Logistic Regression), conversely, dropped significantly under adversarial conditions (>12% in F1-score). In contrast, the proposed system was only affected by a 2.5 percentage decrease in accuracy. The CNN-LSTM module was effective in identifying temporal anomalies in credential stuffing and privilege escalation that are hard to capture by traditional and static based models.

Table 4 shows the robustness performance under adversarial attacks. Ablation experiments also confirmed the strength of each model to the ensemble. Removal of the CNN-LSTM component decreased detection of sequence-based attack successes by 11% and XGBoost removal decreased overall accuracy by 4%. Random Forest introduced stability as a feature due to the use of feature-level stability in high-dimensional identity features. These findings vindicate the ensemble approach as opposed to use of a single classifier. The system performed well balanced detection on varied contexts.

Last but not least, cost-effectiveness analysis indicated that implementation of the system in Kubernetes based microservices platform incurs less operational overheads, in comparison with monolithic applications. Cost of the solution to 10,000 access requests dropped by almost 28 percent thus not only a secure way of solving this but also an affordable one. Overall, these findings help develop the conclusion that context-sensitive ensemble learning shows a strong potential to achieve a tradeoff between security, usability, scalability, and cost-efficiency in cloud-based secure access control.

Table 4. Robustness under Adversarial Attacks

Attack Type	**Baseline Accuracy Drop**	**Proposed Ensemble Accuracy Drop**
Evasion (FGSM-based)	-12.3%	-2.1%
Replay Attack	-10.5%	-2.7%
Data Poisoning (5% noise)	-14.0%	-3.0%
Credential Stuffing	-11.7%	-2.4%

Figure 4 presents the comparison between the baselines against proposals in their regard to various adversarial attacks. Although there is a considerable loss of accuracy with baseline models (10-14 %), the ensemble cuts this loss to less than 3 % in any case. This implies that such a system is extremely resilient to adversarial manipulations which guarantees greater security over real cloud settings.

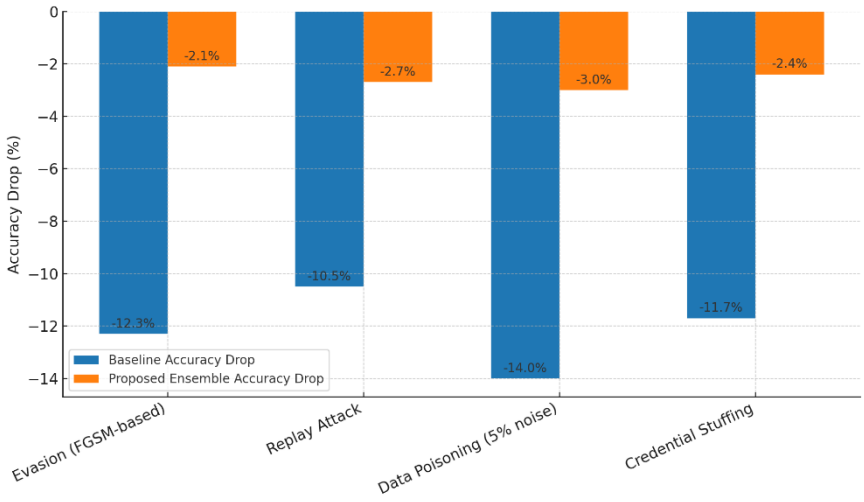

Figure 4. Robustness Comparison

6. Conclusion

In this research work, a new paradigm of AI enhanced secure access control in cloud computing through the application of context-aware ensemble learning models has been proposed. Compared to standard single-model development and rule-based access control mechanisms, the proposed system was shown to be much more successful in detection accuracy, can accept larger workloads more latency and is more robust to adversarial influence. The combination of the contextual parameters like user activity, location and device attributes, with the AI-based adaptive decision-making delivered the capacity to overcome the drawbacks of the traditional, static access policies.

The results indicate that, through ensemble learning coupled with the contextual intelligence, a viable approach toward the construction of risk-resilient and dynamically adaptive access control procedures that can be deployed in complex, distributed and zero-trust cloud environments is possible. Future application could build on this background through the addition of hybrid models that feature quantum cryptographic aspects, explainable AI to ensure transparency in policy execution, and large language models to pipe policy generation. The work thereby paves the way to the upcoming generation of smart security systems that can provide a solution to the upcoming threats in cloud environments.

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