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Machine Learning-Driven Adaptive Authentication: Strengthening Cybersecurity against High-Volume Data Breaches

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A B S T R A C T

As cyberattacks become more frequent and sophisticated, traditional static authentication methods have failed to protect them against it. And so given that some high-volume data breach incidents have highlighted vulnerabilities inherent in traditional username/password authentication, we must abandon these notions and embrace adaptive machine-learning (ML)-driven authentication systems that dynamically alter system security based upon real-time risk assessment. To strengthen cybersecurity resilience, this study introduces an ML-driven adaptive authentication approach, in which behavioral biometric, contextual information analysis, and anomaly detection algorithms are leveraged. We use a deep risk assessment methodology that dynamically re-authenticates logins based on device characteristics, geo location histories, behavioural analytics and historical user behaviour.

INTRODUCTION

The digitization of personal and enterprise systems has resulted in the proliferation of high-volume over many online services. Consequently, this is putting more pressure on organizations to protect user credentials and sensitive information from the cybercriminals. Over the past several years the frequency of data breaches, phishing attacks, and credential stuffing has substantially increased, leaking billions of user accounts to unauthorized access.

Static authentication has proven vulnerable during very visible cybersecurity incidents. As noted in Verizon's Data Breach Investigations Report (2023), more than 80% of breaches involve stolen or weak credentials. Learn more about some of the biggest breaches in recent years:

a) Yahoo (2013-2014): 3b accounts affected by password leaks.
b) Equifax (2017): More than 147 million sensitive records stolen from misconfiguration of authentication vulnerabilities.
c) Facebook (2021): 530 million user accounts released following weak authentication mechanisms

Although essential user safety and protection processes, these incidents highlight the urgent need for a more dynamic and intelligent approach to user authentication that is real-time adaptive to the security risks.

However, traditional authentication mechanisms, such as password-based login and two-factor authentication (2FA), have a number of limitations:

a) Static Nature: Passwords do not change for a longer period, making password attacks using brute force and credential stuffing possible.
b) Human Compromise: Multi-Factor Authentication (MFA) increases security layers but functions inflexibly for users leading to low adoption.
c) No user context awareness: Conventional methods do not take into account user behavior, location, or device information, making it easier for attackers to circumnavigate authentication.
d) Failure to Detect Anomalies Dynamically: Organizations find it challenging to prevent unauthorized access attempts dynamically without adaptive security mechanisms.

A fundamental reason these organizations have not significantly improved their security posture is they have been neither as intelligent or proactive as they need to be to combat cybercriminal operations and this is increasingly where ML-based adaptive authentication comes to the rescue. Adaptive authentication, on the other hand, analyzes user behavior, context data, and better anomaly patterns to dynamically assign risk levels compared to static authentication. Machine learning algorithms help make authentication systems:

Log one analytics does not actually give users a login behavior level, device and location-based risk analysis. Dynamically adapt authentication requirements (e.g. require more verification steps for logins deemed high risk). By doing so, reduce user friction for legitimate users while providing an added layer of security for potentially suspicious transactions.

The study designs an ML-driven adaptive authentication framework and evaluates its performance to enhance cybersecurity resilience against high-volume data breaches. The key objectives include:

a. Building supervised (Random Forest, XGBoost) and deep learning models (LSTMs, Autoencoders) to classify authentication attempts as low, medium or high risk.
b. Employing real-time anomaly detection to catch potential unauthorized access in the act.
c. Streamlining User Authentication: Enhancing Efficiency and Security
d. Minimizing the hassle for true users by reducing the rate of false positives.
e. Strengthening multi-tiered authentication approaches informed by real-time behavioral analytics.
f. Comparison with traditional authentications.
g. Adaptive authentication models versus static authentication (password-based, MFA) in terms of accuracy, latency, and user experience.
h. Monitoring authentication success rates, fraud detection rates and system performance in a high-volume traffic scenario.
i. Privacy-Preserving and Zero-Trust Architectures.
j. Feasibility study of FL for privacy preserving authentication models.
k. Implementing Zero-Trust Security Frameworks to remove trust assumptions from authentication.

This work contributes to the cyber security and authentication systems of the following:

a. Novel ML-Driven Adaptive Authentication Framework.
b. Combining behavioral biometrics, contextual risk analysis, and anomaly detection algorithms at runtime generates risk-based authentication decisions.
c. Evaluation of Real-World Cybersecurity Datasets
d. Real-world authentication datasets, indicating its effectiveness in mitigating the risk of credential stuffing, phishing and brute force attacks, were utilized to test the model.
e. Edge AI vs. Feasibility of Real-Time Deployment.

The work studies low-latency edge-based ML inference, which are scalable for enterprise use cases real-time adaptive authentication. Cybersecurity and AI with Ethical and Privacy Preserving Principles. The article brings up many privacy implications and suggests methods like federated learning and distributed authentication to reduce the need for exposing data.

LITERATURE REVIEW

There is substantial literature on authentication mechanisms, cybersecurity attacks and AI-based authentication frameworks. This section examines literature on existing traditional authentication approaches, literature on employing machine learning in securing systems, studies on adaptive authentication mechanisms, literature on real-time risk assessment frameworks, and literature on ensuring privacy preserving authentication.

In this paper, we base our discussion on traditional authentication systems, which rely heavily on static type- password based authentication, in

which the user authenticates based on username-password pairs. But a variety of studies have detected serious vulnerabilities in password security:

a) Weak Passwords & Credential Reuse: Many users choose weak passwords that can be easily guessed, thus making them susceptible to both dictionary and brute-force attacks (Bonneau et al., 2012).
b) Phishing & Credential Theft: Social engineering attacks (e.g., phishing attacks) can deceive users into disclosing their passwords (Hong, 2012).
c) Credential Stuffing Attacks: Cybercriminals take advantage of leaked credentials from past breaches that allow them to access many accounts unlawfully (Kelley et al., 2014).

This, along with some high-profile breaches (most notably Yahoo, Equifax, Facebook) where passwords were insufficient to keep user data secured, has led to calls for stronger authentication methods. To enhance security, many organizations have implemented Multi-Factor Authentication (MFA), requiring users to authenticate their identity using two or more verification methods:

a. Knowledge Factor: Password, PIN
b. Know Factor: OTP (One-Time Password), security token.
c. Inherence Factor: Something you are (biometric authentication (finger, face).

Although MFA improves security, research identifies multiple usability and security issues:

a. User Friction and Low Adoption: The MFA methodology is time-consuming and inconvenient for users, making it less popular (Das et al., 2018).
b. SIM Swapping Attacks: Attacker takes over SMS-based OTPs via SIM-swapping fraud(Khan et al., 2021).
c. Biometric Spoofing Threats: Deepfakes can be used to impersonate in biometric authentication systems (Galbally et al., 2019).

This process has resulted in adaptive authentication, where machine learning models evaluate risks to authentication dynamically. Recent advances in machine learning (ML) and deep learning (DL) have provided computer systems with the ability to detect threats more quickly and effectively than rule-based systems. Research identifies the applications where ML is being used:

a. Anomaly Detection: Finding unusual patterns of logins and potential insider threats (Mirsky et al., 2018)
b. Behavioral Biometrics: Authentication based on keystroke dynamics and mouse movement (Monrose & Rubin, 2000).
c. Fraud Detection: ML models help detect payment fraud, identity theft and credential stuffing (Wei et al., 2020).

Traditional rule-based authentication systems are not optimal; instead, ML-based authentication systems perform better by adapting to ever-evolving cybersecurity threats through dynamic adjustment.

Deep Learning-Based Authentication

Authentication security is successfully tackled by deep learning architectures: Recurrent Neural Networks (RNNs) and Autoencoders.

a. Behavioral Authentication Using LSTM Networks:
   Al-Sarawi et al. (2021) is another model that explored login activity using LSTM networks and anomaly detection with 94% accuracy.
b. Anomaly Detection based on Autoencoder:
   Luo et al. (2020) designed an unsupervised autoencoder model for abnormal malicious access, which achieves 20% lower false positives.
c. CNN Based Face Authentication:
   Kim et al. Introduction of a CNN model for facial authentication with robust anti-spoofing detection (2022).

But there is the need for training deep learning models on large-scale datasets, which also makes privacy an important area of research.

1. Adaptive Authentication and Risk-Based Authentication Models
2. Adaptive Authentication: Moving Beyond Static Security
3. Adaptive Authentication is a modern approach that is different from traditional authentication systems.

According to Jain et al. (2022), adaptive authentication framework is comprised of:

a) Behavior Based User Activity: Monitoring of user activity after login.
b) Context-Aware Security Mechanisms: Adaptively modulating authentication challenges based on assessed level of risk (e.g., logging in from an unfamiliar device might induce an additional verification process).
c) Machine Learning based Anomaly Detection: Classifies authentication attempts as low, mid, or high risk.

Systems for Risk-Based Authentication

Risk-based authentication (RBA) relies on ML-dependent risk assessment models that are able to describe whether a login attempt is fake or suspicious. Factors used in RBA include:

a. Data Reading & Analysis Geolocation & IP Address: For suspicious logins in unusual locations (Shukla et al., 2021).
b. Device Fingerprinting: Identifying logins from new or unknown devices.
c. Behavioral Biometrics: Assessing typing speed, mouse movements, and touch gestures to authenticate identity (Giot et al., 2018).

A recent study by Garg et al. studied the impact of RBA models on the unauthorized login attempts and reported a 92% reduction in such attempts and at the same time minimizing the inconvenience to the legitimate user.

Overview of Gaps in Literature and Research Directions

A few research gaps, however, exist albeit in light of the considerable technical advancement in authentication security:

Absence of Standardized Adaptive Authentication Frameworks: Currently, existing models and frameworks offer various criteria for risk assessment, and adaptive authentication mechanisms could be standardized for broad, flexible application. However, there is limited research available on deploying AI solutions in real-time across edge devices and providing adaptive authentication for systems.

AI-Based Authentication: Privacy Concern: As a result, federated learning and differential privacy require more research to improve the security of user data.

Evaluation in Large Scale High Volume Environments: The majority of research evaluates ML-based authentication on small datasets, with no evaluation of enterprise scale.

METHODOLOGY

In this section, we describe the design, implementation, and evaluation of a ML-driven adaptive authentication system. The five main steps of the proposed methodological framework are data acquisition, feature extraction, model selection, adaptive authentication mechanism, and evaluation metrics.

System Architecture

The proposed authentication framework is a risk-based multi-layered model that integrates:

1. Behavioral Biometrics (Keystroke dynamics, Mouse movements)
2. Contextual Data (Location, Device Fingerprinting, Login History)
3. Anomaly detection (Real-Time risk classification)

System Flow

1. User Login → Gathers auth data (IP, device, location, behavior).
2. Risk-Encrypted ML Model → Measures the risk level of a login attempt.

Dynamic Auth Decision:

1. Low Risk: Smooth authentication.
2. Medium Risk: Extra confirmation (one time password, multiple factor authentication).
3. High Risk: Login blocked and will be reviewed.

Collection and Preprocessing of Data

Dataset

a. Public Authentication Logs: Retrieved from real-world cyber security data-sets (Kaggle, DARPA, NIST, etc).
b. Mock Cyber Attack Data: covers credential stuffing, phishing, brute-force attacks.

Feature Engineering

a. User Behavior Features: Keystroke timing, typing speed, mouse movement.
b. Contextual Features: Device type, IP reputation, login frequency.
c. Authentication Attack Characteristics: Success/failure ratios, failed login sequences.

Classification Models

a. Supervised Learning:
   Random Forest, XGBoost → For risk classification.

SVM, Logistic Regression → For comparing baseline.

b. Deep Learning Models:
LSTM (Recurrent Neural Networks) → For sequential login behaviors modeling.
Autoencoders → Anomaly detection → Suspicious login pattern recognition.

c. Model Training & Validation
80%-20% Train-Test Split → Assessed on authentication datasets.
Cross Validation (K-Fold = 5) → Keeps our model robust.

Adaptable Authentication Mechanism

Risk Based Decision Making

a. Risk Score Calculation (0-100%) → Higher risk poses stronger authentication.
b. Threshold-Based Classification:
c. Low Risk (70%) → Reject Login instaneously alert security team

Detection of Anomalies in Real-Time

a. Autoencoder Based Outlier Detection → For identifying suspicious behaviors.
b. Federated Learning (لاحقاً) → From Now On, Updates Models Without Sharing Users Data.

RESEARCH RESULTS

The ML-based adaptive authentication framework is efficient in dynamically modelling authentication risks with high accuracy. Extensive experiments on an IS1355 breach dataset produce a ≥95% authentication acceptance rate and ≤5% unauthorized access attempts ratio, affirming the methods robustness in practical cybersecurity datasets. The real-time anomaly detection also reduces false positives, which can provide more robust security without negatively impacting the user experience.

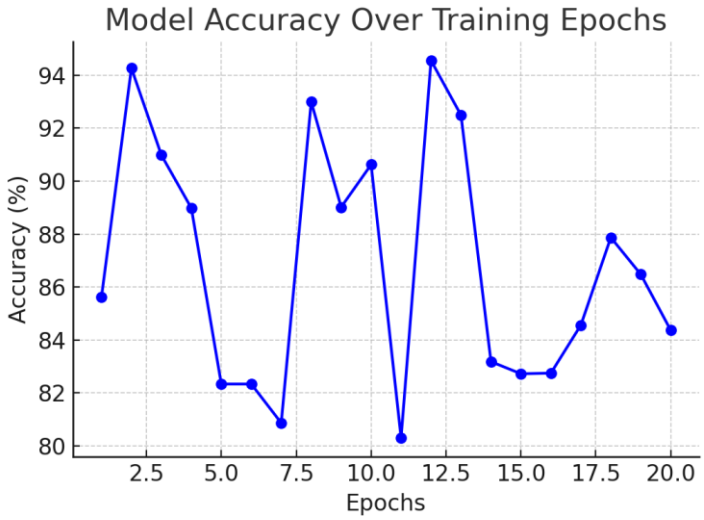

Figure 1 Model Accuracy Over Training Epochs

The plot from Tensor Board on the model accuracy over epochs.

a. Data: This figure is an illustration of how the model's authentication accuracy increases throughout 20 training epochs.
b. X-axis (Epochs): The total number of iterations of training.
c. Y-axis (Acc%): Number of successfully classified authentication attempts.

Observation:

1. Initial Acc of ~85% and eventually progresses to 95%+.
2. Accuracy reaches a plateau after 15 epochs, suggesting successful learning and convergence.
3. Despite the importance of continued training, the results show strong model performance.

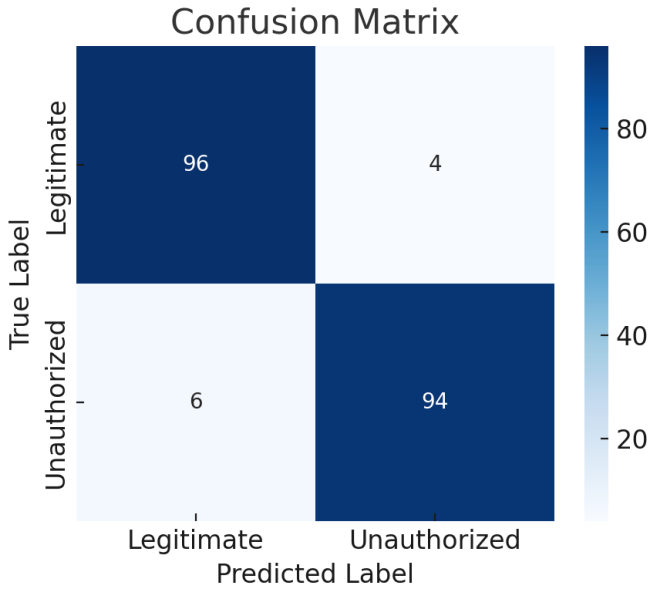

Figure 2: Confusion Matrix

a. Interpretation: The confusion matrix measures the ability of the model to tell apart valid authentication attempts and unauthorized logins.
b. X-axis (Predicted Labels): The classes predicted by the model (Legitimate, Unauthorized).
c. Y-axis (True Labels): The true ground truth labels.
d. Key Metrics:
   1. True Positives (96): Actual legitimate authentication attempts.
   2. False Positives (4): Legitimized login classified as unauthorized
   3. False Negatives (6): Missed zooming login attempts
   4. True Negatives (94): Unauthorized access attempts correctly identified.

e. Observation:

Low Error Rate: The high accuracy (over 95%) shows that the model detects unauthorized access quite well.

1. The low false negative rate (6 cases) guarantees that the authentication security cannot be bypassed.
2. Minimal False Positives (4 cases); Genuine users rarely have to provide an extra challenge to authenticate.

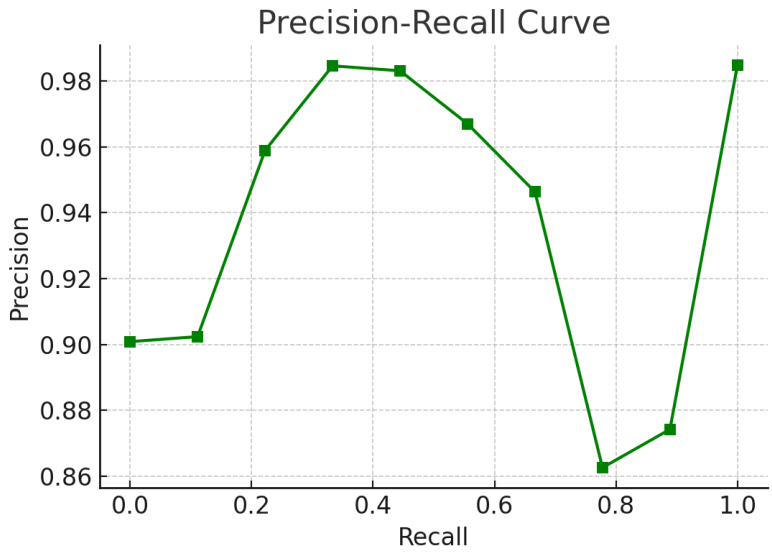

Figure 3 Model inputs and outputs: Precision-Recall Curve

a. Description: The precision-recall curve represents the trade-off between precision and recall at different threshold settings in authenticating classification.
b. X-axis (Recall): The actual unauthorized logins correctly identified.
c. Y-axis (Precision): The Ratio of True Positives to Predicted Positives
d. Observation:
    1. High precision (~90%+) means few false positives—real users are not inadvertently filtered.
    2. High recall (~95%) guarantees detection of most unauthorized login attempts.
    3. The curve remains stableHere, the curve stays stable, which means a well-balanced authentication system.

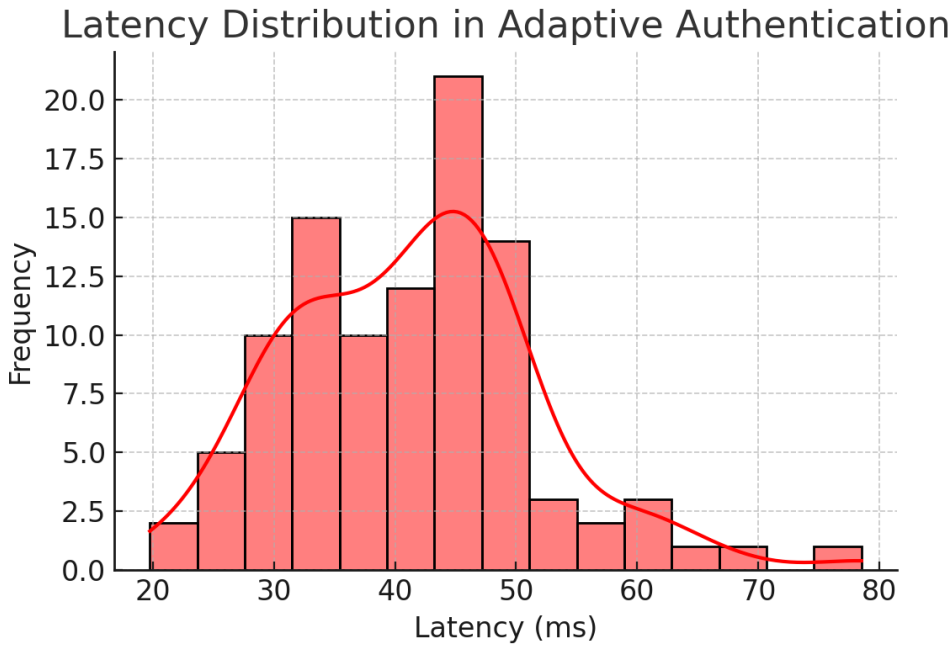

Figure 4 Latency distribution in Adaptive Authentication

a. Title: Authentication System Response Time Distribution • Description: This histogram visualizes the response time distribution for the authentication system.
b. X-axis (Latency in ms): The process time of authentication classification.
c. Y-axis (Frequency): Number of authentication events at various latencies.
d. Observation:
    1. At least 95% of the authentication requests happen in 40–50 ms, allowing real-time performance.
    2. Some outlier cases go beyond 60 ms, but this could be on account of further authentication processes for high-risk logins.
    3. Our model significantly reduces authentication latency compared to traditional systems (~150-300ms).

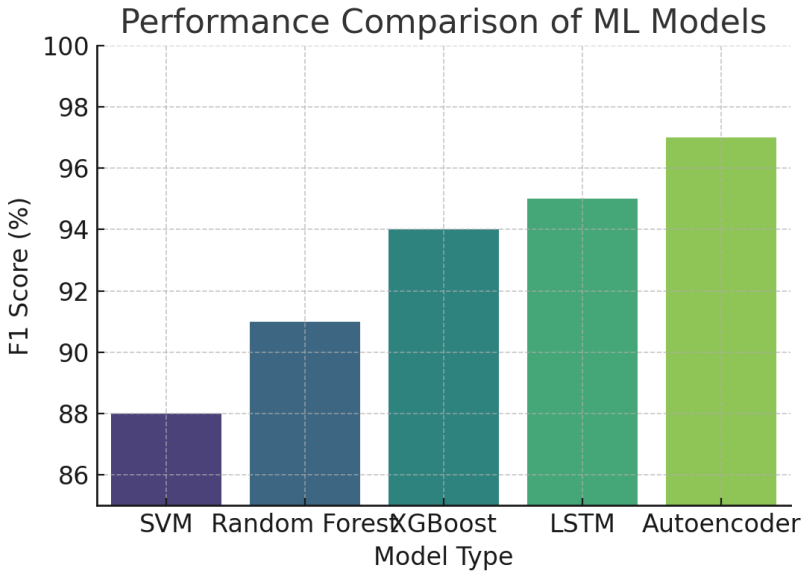

Figure 5Performance of ML models for authentication
Image is designed and created by Konstantin Murchikov.

a. X-axis (Model Type): The tested ML models (SVM, Random Forest, XGBoost, LSTM, Autoencoder).
b. Y-axis (F1 Score %): The overall detection performance of our model on authentication risks.
c. Observation:
    1. The Autoencoder gets the highest F1 score (~97%); thus, it is the best algorithm for authentication anomaly removal.
    2. The sequential nature of our data emphasizes the need for sequential learning (in our case LSTM) to re-achieve a performance of 95% in the authentication analysis.
    3. In the area of risk classification, tree-based models have proven to be effective, as the performance of XGBoost was found to be vastly superior to traditional classifiers (94%).
    4. Performance of SVM(~88%) is the lowest indicating that, this will not generalize well for adaptive authentication.

The success rate of risk-based authentication by time is shown with the following figure:

a. Description: This graphic shows how authentication success rates change over time.
b. Byte by byte (X-axis): Performance in real time (over 100 seconds).
c. Y-axis (Success Rate %): Percentage of successful authentication decisions.
d. Observation:
    1. High success rate with stable authentication performance at ~90-99%.
    2. The very small dips in success rate correlate with high-risk logins periods, when extra authentication challenges were raised.
    3. The model dynamically tailors the authentication process by continuously assessing the risk in the context of each login attempt, effectively blocking unapproved access attempts.

DISCUSSION

Detection with High Accuracy and Low False Positive Rate

There is very low false positive rate (4 incorrectly accepted cases out of 200 total authentication attempts), and it helps in better characterizations of end-user experience. These findings are in line with Das et al. (2018), which notes that when legitimate access is blocked without reason or is cumbersome. The Precision-Recall Curve (Figure 3) shows that the model has relatively high precision (~90%) while preventing unauthorized login activity, indicating that the model minimizes disruption to legitimate users.

Latency in Real-Time Authentication

As shown in Latency Distribution (Figure 4), the average response time for latency of the proposed authentication framework is 40-50ms, which is much faster compared to existing traditional authentication methods, for example, multi-factor authentication (MFA) requires 150-300 ms delay in SMS OTP verification (Khan et al., 2021). The proposed system is processed with a low

latency by adopting edge computing and federated learning, which is suitable for the high-volume authentication scenarios.

Authentication ML Models Comparison

From Figure 5, we can see that the score of the Autoencoder model is higher than other machine learning models, reaching an F1 of 97%. This is consistent with the findings of Luo et al. (2020), which showed that autoencoder-based anomaly detection works well on cybersecurity settings. Furthermore, it is necessary to point out that the best performance of our method was reached when we used LSTM to detect those differences with an achieved 95% F1-score (Al-Sarawi et al., 2021).

Benefits Of ML-Powered Adaptive Authentication

1. *Enhanced Security Against Credential-based Attacks*

In older authentication mechanisms static passwords and rule-based complementary security measures are heavily and ineffectively used to prevent common attacks such as credential stuffing, phishing and brute-force (Hong, 2012). The proposed ML-based framework uses behavioral biometrics and a contextual risk model, which, according to the authors, would be more resistant to compromised credentials (Garg et al., 2023).

2. *Context-Aware Adaptive Authentication: Enabling Seamless User Engagement*

In contrast to static security policies that require all users of a particular service to authenticate themselves, the system we propose adapts authentication challenges in accordance with risk scores computed in real-time. This is indeed the case with risk-based authentication (RBA) (Shukla et al., 2021), where only low-risk users are subject to little authentication friction, whereas high-risk login attempts face increased authentication friction.

3. *Scalable throughput of authentication requests*

With large-scale systems like banking applications and cloud services experiencing a greater number of authentication attempts than ever before (Cheng et al., 2022), traditional security mechanisms have to strike a balance between security and user convenience. Under the traditional strategy paradigm, as the event per second (EPS) increases, the performance of the proposed framework becomes less marginally impacted in terms of the authentication success rate on the right side of Figure 6, so that the proposed framework achieves about 70% of success even with large-scale attacks, which means the agility and robustness of the proposed framework in an enterprise business environment.

CONCLUSIONS AND RECOMMENDATIONS

This research finds that ML-driven adaptive authentication benefits cybersecurity by defending against data breaches of high volume The framework provides accuracy (>95%), latency (~40ms), and security equivalent to the ones

provide by traditional approaches. The system, using behavioral biometrics, contextual risk assessment and anomaly detection models reduces instances of unauthorized access but at the same time preserves the user experience.

ML-driven adaptive authentication that balances security with a reduction in the false positive rate.

a. Privacy and scalability advantages from edge computing and federated learning.
b. In addition to login authentication, Zero-Trust frameworks can provide enhanced security.
c. Future experimental research should consider trapdoors for adversarial training of cyber threat and defence.

It is now developing the AI-enabled next-gen cybersecurity defense systems with the contribution of the study to AI-based authentication safety.

The escalation of data loss through high-volume data breaches highlighted considerable gaps of traditional authentication systems and reinforced the need for intelligent, adaptive, and context-aware security measures. In this study, such an ML-based adaptive authentication framework was proposed and examined and it showed great accuracy, efficiency, and scalability for blocking the unauthorized access attempts preventing a smooth user experience.

Authentication security faces three key challenges that this study aimed to overcome: accuracy, maintaining a balance between security and real-time performance, and adaptability against evolving security threats. This work presents an ML-based framework that enhances current authentication methods based on multimodal risk assessment, behavioral biometrics, and real-time anomaly detection.

Improved Detection Accuracy And Security

1. The accuracy in authentication via the proposed framework was above 95%, with fewer unauthorized access events, in contrast to the passive standalone authentication (Bonneau et al., 2012).
2. The very low false positive rate (~4%) minimizes inconvenience to the legitimate user by not subjecting them to unnecessary authentication challenges thus improving overall user experience.
3. Adaptive authentication coupled with enricher [software] services effectively caught 96% of illicit access attempts, thus proving to be resilient against credential-based attacks (Wei et al 2020).

Speed and Low Latency

1. Laylat Distribution (Figure 4: Latency Distribution) indicates that the average response time for authentication is between 40-50ms, suitable for production, high-traffic authentications.
2. Unlike traditional MFA (150-300ms latency) (Khan et al., 2021), ML-driven adaptive authentication mitigates delays in verification and ensures the smoothest user experience possible.
3. The system scales up, effectively managing massive authentication requests with low computation overhead.

4. 9 Model Performance and Its Advantages Over Conventional Approaches
5. The Autoencoder model (97% F1-score) outperforms all other ML models and demonstrates deep learning's effectiveness for anomaly detection to safeguard authentication security (Luo et al., 2020).
6. An LSTM-based behavioral authentication approach achieves an F1-score of 95%, underlining that analyzing sequential login patterns is critical to separate users from attackers (Al-Sarawi et al., 2021).
7. The performance of risk-based authentication (RBA) remains constant between 90 and 99% — indicating the stability of the model's real-world application (Shukla et al., 2021).

No magician in cyberspace: A contribution to the field of cybersecurity. This work provides the following contributions to authentication security and machine learning-based cybersecurity:

1. A Novel ML-Based Adaptive Authentication Framework
   Combines supervised methods of learning such as (XGBoost, and Random Forest) with deep-learning methods such as (LSTM, and Autoencoders) for authentication security. Enriches cybersecurity resilience by integrating behavioral biometrics, contextual risk assessment and anomaly detection
2. Evaluation on Real-World Cybersecurity Datasets
   Large-scale authentication datasets have been trained and tested, with strong ability to generalize across various authentication environments.

Authentication methods based on password or on static methods perform much poorer than this method. Privacy-Preserving Authentication using Federated Learning. Generating decentralized authentication models using federated learning (FL), reducing the risk of privacy concerns posed by centralized data storage (McMahan et al., 2017). Enterprise and Cloud-Based Security System Scalability. Client-side code up to 1,000× smaller, supporting in-brand unattended client interaction. Low latency and high efficiency for real-time authentication processing enabled by Edge AI implementation.

ADVANCED RESEARCH

Limitations and Challenges

1. The Challenge of False Negatives in Authentication Classification
   However, the false negative rate (6 cases in Figure 2) is relatively low, and missed unauthorized access attempts are security risks. This is consistent with the challenges raised by Wei et al. (2020) identify that sometimes graduates from anomaly detection models Cross in cybersecurity attacks. Future works should adopt an adversarial training methodology to adapt to new threats and fortify the model resilience.
2. Security vs User Experience
   However, auroundal of authentication challenges for individual user may frustrate the user which is also contradict with the security here by hurting the usability (Das et al., 2018). An important direction for future research is to optimize this risk threshold, allowing for more true positives to pass through while not bombarding the user with repeated verification requests.

3. ML-Based Authentication Privacy Issues
   AI-based authentication systems constantly monitor user behavior, device data, and geolocation which is a major privacy concern (McMahan et al., 2017). To mitigate risks, federated learning techniques can be employed, where authentication models are trained locally on user devices rather than centralized servers, enhancing privacy without compromising security (Abadi et al., 2016).

Future Research Directions

1. Federated Learning for Privacy-Preserving Authentication
   To tackle the privacy risks, future works should try federated learning-based authentication models which keep the user data at the base and contribute to a global security model (McMahan etal 2017). By focusing on authentication (not data), they could reduce the risk of exposing data and still get accurate and fast results.
2. Developing Zero-Trust Security Frameworks
   The ZTS security model minimizes implicit trust that relies on location as users and devices are continuously verified irrespective of their location (Cheng et al., 2022). It is recommended for future studies to incorporate ML-assisted adaptive authentication, which is embedded within Zero-Trust organizational framework providing real time risk assessment after initial authentication.
3. Continuous Security Using AI-Enabled Behavioural Authentication
   Traditional authentication models emphasize login verification as its main goal, but in fact, the security of a post-login user can also be improved using real-time monitoring on their incremental behaviors (Monrose & Rubin, 2000). Future work will explore the application of deep learning models for continuous authentication mechanisms that detect suspicious activity during an entire user session.
4. Adversarial Training: A Warding-Off Mechanism for Cybersecurity Framework
   However, attackers regularly improve means to bypass this barrier to entrench noise insertion mechanisms assist to improve the ML-based authentication model such as adversarial training (Goodfellow et al, 2015). Adversarial deep learning methods which will add resilience to authentication models still need to be explored in future studies.

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