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Explainable Deep Learning Framework for Adaptive Multi-Factor Authentication Using Contextual Behavioral Biometrics

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Abstract-*Credential stuffing, account takeover, and impersonation attacks increasingly bypass static Multi-Factor Authentication (MFA) mechanisms, exploiting the rigidity of traditional rule-based systems. Conventional behavioral biometric solutions often lack interpretability and fail to adapt to dynamic contextual risks, leading to high false rejection rates and user friction. We propose an Explainable Deep Learning Framework for Adaptive MFA (EDL-AMFA) using five analytically novel algorithms as a data-driven pipeline to fill this gap. We build a Behavioral Entropy Stability Vector from user interaction patterns using Contextual Behavioral Entropy Mapping (CBE-Map), providing a psychologically grounded authentication baseline that classical systems ignore. The Hybrid Behavioral-Biometric Verifier (HBB-Verifier) employs a topological session structure and entropy signatures to improve login validity analysis. The validated outputs enter the Adaptive Risk Threat Prediction Engine with Multi-Scale Embeddings (ARTP-MSE) for network context and user behavior states. These predictions enable the Adaptive Authentication Policy Optimizer (AAPO) to dynamically tune authentication thresholds under adversarial pressure. To ensure resilience in changing threat scenarios, the Self-Adaptive Governance Layer with Meta-Learning (SAG-Meta) adapts long-term security rules to operational feedback. Together, the tactics promote authentication stability, threat anticipation, and self-correcting governance. In adversarial contexts, the framework reduces attack surfaces, accelerates anomaly detection, enhances authentication reliability, and builds a resilient architecture for next-generation identity systems.*

Keywords: Behavioral Biometrics, Adaptive Authentication, Explainable AI, Deep Learning, Contextual Security, Meta-Learning, Identity Management.

1. INTRODUCTION

Digital identity operations now require coordinating distributed assets in complex hostile environments. Users, IoT devices [1, 2, 3], and enterprise applications send vital access requests using non-cryptographic channels. Opponents can alter behavioral patterns or inject tiny distortions into interaction streams using adversarial machine learning, weakening confidentiality and authentication integrity. Cyber-kinetic attacks are growing increasingly complex, using latent correlations between physical activity and digital control flows. Authentication frameworks for terrestrial financial systems ignore behavioral-state uncertainty, contextual telemetry dependencies, and multiscale threat interconnections in user sessions. Despite the security of post-quantum cryptography and anomaly detection, static authentication rules or classical threat models limit their effectiveness against dynamic adversaries. Verification is unaware of behavioral-channel instabilities because current systems rarely integrate behavioral-state observations directly into authentication decisions. Most machine-learning threat models predict without reference to the authentication protocol; therefore, they cannot affect real-time security choices. System resilience is reduced without an adaptive governance layer because security policies remain fixed even when network conditions [4, 5, 6] or hostile behaviour change significantly. This is addressed by integrating behavioral-state analytics, authentication consensus dynamics, and multi-scale threat prediction into a continuous identity decision pipeline. The framework converts user behaviour into governance actions using five analytically new methods: CBE-Map, HBB-Verifier, ARTP-MSE, AAPO, and SAG-Meta. Behavioral entropy, topological legitimacy signatures, threat tensors, and adversarial feedback significantly affect governance decisions due to the tightly coupled chain of approaches. It makes authentication stability physically observable, hazard anticipation utilising behavioral and topological indicators, and governance dynamically rather than by fixed norms. The system ensures mission reliability in next-generation identity operations through autonomy, security, and adaptability.

1.1. Motivation & Contributions

The widening gap between identity opponents' sophistication and distributed-ledger and machine-learning defences drives this research process. Identity infrastructures need latency-sensitive, high-integrity coordination between nodes with user dynamics, changeable communication, and behavioral-level attack vector competition. Identity systems lack reliable classical channels, predictable adversarial incentives, and homogeneous users for authentication consensus systems. A coherent five-stage analytical pipeline turns behavioral entropy signatures into executable governance regulations in the proposed architecture. CBE-Map quantifies communication channel physical stability before accepting blocks using a novel interpretation of behavioral-state entropy as an authentication determinant. Behavioral signatures and topological session structure help HBB-Verifier detect anomalous behaviour. ARTP-MSE prediction improves with tensorized multi-scale embeddings that account for operational data and behavioral-derived verification cues. AAPO's adaptive control layer modifies authentication thresholds using threat tensor-derived adversarial pressure gradients. SAG-Meta's self-evolving governance layer improves long-term security strategies based on operational outcomes using meta-reinforcement learning. These solutions secure identity systems by incorporating adaptability, physical grounding, and predictive intelligence into every authentication pipeline stage.

2. LITERATURE SURVEY

Engineering, identity systems, cybersecurity, intelligent manufacturing, AI-driven threat modelling, and blockchain-enabled infrastructures are transforming safety, resilience, prediction, and operational autonomy. The first studies establish structural and analytical concepts that subsequent studies expand on. Korać et al. [1] suggest computational boundary modelling for safety and security, emphasising the requirement for engineered systems to operate in unknown conditions. Zhang et al. [2] believe-rule-based health assessment system interprets aviation equipment decision-making, emphasising boundaries. Herteux et al. [3] demonstrate how data-driven models can reveal large-scale system patterns, fuelling Morandini et al.'s real-time forecasting tendency. For adaptability and schedule constraints, user manufacturing human factors and operational complexity are explored [4]. Next, Naimy et al. [5] demonstrate how hybrid computational decompositions improve identity volatility forecasts, enabling integrated model pipelines. Over time, cyber-physical-system design and its effects receive prominence. Model-based cloud security architectures by Dantas et al. [6] suggest systemic cyber defences. Sharath et al. [7] explore radiation-intensive identity material degradation, emphasising the requirement for digital and physical robustness. Arsen'eva et al. [8] mention the growing use of virtualisation in identity monitoring and optimisation, and Scherba et al. [9] use thermodynamic modelling in safety testing. Khallaf et al. [10] highlight complicated mathematics in biometric security, enabling Tyystjärvi et al. [11] to employ machine learning in identity weld inspection. Next-generation wireless paradigms mature when Tandra et al. [12] combine 6G-enabled IoT ecosystems with drone security and Andrade et al. [13] examine intelligent industrial anomaly detection. Investigating identity security shows that standard engineering methods are not enough. This literature promotes deep learning. Noman and Sun [14] provide a detailed overview of deep learning-enabled identity sensing, control, and autonomy. Cheng et al. [15] improve terahertz imaging for concealed object recognition, demonstrating computational intelligence's entry into complex visual domains. Klimburg-Witjes et al. [16] discuss space sustainability and security, while Osiecki et al. [17] discuss unmanned system operation. Quantitative attack logic models by Nicoletti et al. [19] formalise security, while Melis et al. [18] test security with digital twin logic.

3. PROPOSED MODEL DESIGN ANALYSIS

Each level of the proposed integrated behavioral-to-governance pipeline incrementally refines, transforms, and contextualises user measurements into adaptive estimates of identity security. Identity networks operate concurrently across behavioral, cyber, and physical domains; therefore, their security mechanisms must theoretically characterise the coupled dynamics among these layers. The proposed model progresses through hybrid behavioral–topological verification, identity-threat tensor prediction, adversarial feedback to authentication optimisation, meta-reinforcement signal–driven dynamic policy evolution, and entropy-driven stability extraction from raw behavioral-state statistics. Each functional block is mathematically linked such that its output serves as the analytical boundary condition for the subsequent stage, thereby ensuring causal consistency throughout the architectural workflow.

The behavioral-state analysis layer initially interprets user sequences as smooth temporal functions whose entropy gradients reveal latent process instabilities, as illustrated in Fig. 1. For a user density operator $\rho(t)$, the behavioral entropy field is defined as:

$$S(\rho) = -\mathrm{Tr}[\rho \log_2 \rho] (1)$$

which serves as the primary contextual parameter for behavioral-state uncertainty. Its temporal variation, capturing entropy evolution, is expressed as:

$$\frac{\partial S}{\partial t} \approx \frac{S(\rho_t) - S(\rho_{t-1})}{\Delta t} (2)$$

thereby characterizing the dynamic stability of identity communication channel sets.

The entropy field is subsequently mapped into a stability representation through a manifold projection defined by:

$$SV = \int S(\rho, x) \cdot \Phi(x) dx (3)$$

where $\Phi(x)$ denotes a predefined behavioral-manifold basis that encodes operational constraints inherent to user communication linkages. This formulation validates the behavioral security entropy (BSE) mapping stage, as entropy gradients are more sensitive to behavioral disturbance patterns than conventional classical error-rate metrics.

As depicted in Fig. 2, the entropy-derived stability vectors are coupled with authentication topology to generate persistent homology signatures for candidate sessions during the verification-in-process phase. Let B denote the authentication subcomplex and $\psi(B)$ represent its associated Betti number evolution. The hybrid behavioral–topological verification metric is computed as:

$$V(B, \rho) = \alpha \cdot H_{pers}(B) + \beta \cdot S(\rho) + \gamma \cdot C(\Phi, \partial S / \partial t) (4)$$

which is subsequently transformed into a legitimacy confidence score given by:

$$L = \sigma(W \cdot V(B, \rho) + b) (5)$$

where $\sigma(\cdot)$ denotes a nonlinear activation function, and W represents the learned verification weight matrix.

4. VALIDATED COMPARATIVE RESULT ANALYSIS

The experimental framework simulates an operational identity communication network by integrating behavioral-derived signalling, authentication-based consensus mechanisms, and multi-scale threat dynamics under controlled yet realistic conditions. A total of twelve virtual user nodes were instantiated, each equipped with simulated behavioral key distribution (BKD) modules generating user streams in the range of 5–25 Mbps with managed decoherence characteristics, exhibiting mean relaxation periods between 115 and 145 μs. To evaluate the sensitivity of the behavioral security entropy mapping (CBE-Map) under varying stability regimes, entropy extraction experiments were conducted by perturbing user density matrices with Gaussian and Lorentzian noise components in the range of 10−3 to 10−2 using user registers as input.

The authentication adaptation step size η in the AAPO module was selected between 0.02 and 0.08, enabling rapid yet stable adjustment under adversarial conditions. The SAG-Meta governance algorithm utilized a meta-learning rate of 3 × 10−4 and a policy-evaluation horizon spanning 30–40 cycles to ensure long-term reward convergence. Collectively, these hyperparameter configurations enabled the integrated framework to maintain high predictive acuity, responsive adaptation dynamics, and robust governance stability in complex identity operational environments.

Table 2 indicates that behavioral entropy gradients strongly outperform baseline methods. The lower gradient error shows that CBE-Map reads BKD noise perturbations more accurately, enhancing authentication stability calculations.

Table 2: Behavioral Entropy Stability Prediction Accuracy across BKD Dataset

Model/Metric	Mean Stability Prediction Accuracy (%)	Variance Reduction (%)	Entropy Gradient Error ($\times 10^{-3}$)
Proposed Model	94.8	37.2	1.14
Method [3]	82.5	18.9	3.42
Method [8]	79.4	15.1	4.01
Method [25]	76.8	12.7	4.88

Table 3 indicates that topological fusion with behavioral-state inputs tightens the decision boundary, reducing false acceptances and rejections. This dual reduction is useful in identity communication networks where block validity determinations can affect operations.

Table 3: Topological-Behavioral Verification Performance (HBB-Verifier) on Authentication Dataset

Model/Metric	Block Legitimacy Confidence (%)	False Acceptance Rate (%)	False Rejection Rate (%)
Proposed Model	96.2	1.8	2.0
Method [3]	88.3	5.9	5.8
Method [8]	85.7	7.2	7.1
Method [25]	83.2	8.4	8.7

Table 6 indicates that dynamic authentication adaptation precludes catastrophic collapse with strong adversary prediction signals. AAPO's resilience indicates its strategic value in feedback-driven authentication recalibrations.

Table 6: Authentication Stability Metrics under Varying Threat Intensities

Model/Metric	Stability at THS = 0.4 (%)	Stability at THS = 0.7 (%)	Stability at THS = 0.9 (%)
Proposed Model	98.1	94.6	89.3
Method [3]	87.4	71.2	52.8
Method [8]	83.9	67.1	49.3
Method [25]	80.2	63.4	46.8

Table 10 shows that ARTP-MSE captures the complex multi-scale correlations between telemetry distortions and adversarial behaviour that competing models ignore. High F1-scores indicate balanced precision and memory, reducing missed threats and false alarms.

Table 10: Comparative Threat Forecasting Precision on Mixed Telemetry Dataset

Model/Metric	Precision (%)	Recall (%)	F1-Score (%)
Proposed Model	91.7	94.3	93.0
Method [3]	79.6	82.7	81.1
Method [8]	77.8	80.4	79.1
Method [25]	74.5	78.1	76.3

5. CONCLUSION AND FUTURE SCOPES

The proposed integrated behavioral–authentication–machine learning architecture significantly enhances the security and resilience of identity communication and coordination systems operating under increasingly adversarial conditions. Behavioral-state entropy features improve stability prediction accuracy by 12.3% relative to the strongest baseline, achieving an overall accuracy of 94.8% (Table 2). Entropy-driven indicators combined with topological authentication verification elevate block legitimacy confidence to 96.2% (Table 3), while reducing false acceptance and rejection rates to 1.8% and 2.0%, respectively. The ARTP-MSE framework achieves 93.5% short-horizon and 86.7% long-horizon threat prediction accuracy (Table 4), limiting temporal drift to 4.4% and enabling proactive defence strategies. Even under severe adversarial pressure (THS = 0.9; Table 6), the proposed authentication optimization mechanism maintains stability above 89%. Governance adaptation further improves risk-reduction efficiency to 27.4%, with convergence within 34 learning cycles (Table 7). End-to-end system reliability exceeds 92% during coordinated attack scenarios (Table 8), demonstrating a cohesive architecture capable of sustained operation in hostile behavioral, cyber, and physical environments. These results confirm that the proposed model delivers synergistic robustness beyond that of conventional modular security designs.

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