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Article

AI-POWERED CYBERSECURITY FOR 7G-ENABLED VIRTUAL THERAPY PLATFORMS: A MACHINE LEARNING FRAMEWORK FOR THREAT DETECTION AND PRIVACY PRESERVATION

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Abstract: The emergence of 7G networks is transforming virtual therapy platforms by enabling ultra-low-latency, high-bandwidth, and immersive healthcare experiences through augmented reality (AR), virtual reality (VR), and haptic feedback technologies. However, this convergence of hyper-connectivity and sensitive healthcare data substantially expands the cyber-attack surface, introducing unprecedented threats including data breaches, adversarial AI attacks, deepfake impersonation, and privacy violations. This paper proposes a comprehensive AI-driven cybersecurity framework specifically designed for 7G-enabled virtual therapy platforms. The framework integrates five interconnected layers: Predictive Threat Detection System (PTDS) employing LSTM and clustering algorithms, Adaptive Threat Intelligence System (ATIS) incorporating Generative Adversarial Networks (GANs), Privacy-Preserving Data Management (PPDM) utilizing federated learning and homomorphic encryption, Continuous Authentication System (CAS) leveraging biometric and behavioral profiling, and a Self-Healing Cybersecurity System (SHCS) powered by reinforcement learning. Experimental evaluation in a simulated 7G environment demonstrates a threat detection accuracy of 98.5%, a 35% reduction in response time compared to conventional systems, and robust privacy preservation compliant

with GDPR and HIPAA regulations. The framework establishes a foundation for secure, resilient, and trustworthy next-generation digital mental healthcare delivery.
Keywords: 7G Networks, Virtual Therapy, Cybersecurity, Machine Learning, Federated Learning, Privacy Preservation, Threat Detection, Continuous Authentication

1. INTRODUCTION

1.1 Background and Motivation

The paradigm shift from 5G/6G to 7G networks marks a revolutionary advancement in communication technology, characterized by ultra-high speed, near-zero latency, and hyper-connectivity. These capabilities are unlocking transformative possibilities in healthcare, particularly in the domain of virtual therapy platforms. These platforms enable patients to access mental health counseling, rehabilitation, and physical therapy remotely through immersive AR/VR environments enhanced with haptic feedback, providing real-time, personalized therapeutic experiences that rival in-person sessions .

However, the very features that make 7G-enabled virtual therapy revolutionary—continuous data streaming, biometric monitoring, and real-time interaction—also create substantial cybersecurity vulnerabilities. Unlike traditional healthcare systems, these platforms process highly sensitive data categories including video and audio communications, physiological responses, behavioral patterns, and biometric information such as facial recognition, heart rate, eye movement, and gestures . The attack surface encompasses data interception during transmission, unauthorized access to health records, denial-of-service attacks, adversarial AI threats, and privacy breaches that could compromise patient safety and trust.

Traditional security models relying on one-time password verifications or static firewall configurations are inadequate in this dynamic environment where data flows continuously and therapy sessions involve real-time interaction through immersive technologies . Furthermore, attackers are increasingly employing AI to generate convincing spoofing content and malware that blends into normal traffic patterns, necessitating a shift from reactive to proactive cybersecurity approaches .

1.2 Research Objectives and Contributions

This research addresses the critical need for robust cybersecurity frameworks for 7G-enabled virtual therapy platforms through the following objectives:

1. Proactive Threat Detection: Develop advanced machine learning algorithms for real-time anomaly detection and predictive threat identification in 7G network environments.
2. Continuous Authentication: Design mechanisms for persistent user verification throughout therapy sessions using biometrics, keystroke dynamics, and behavioral profiling.
3. Privacy Preservation: Implement state-of-the-art privacy-preserving techniques including federated learning, homomorphic encryption, and differential privacy to ensure regulatory compliance.
4. Self-Healing Capability: Enable autonomous detection, containment, and recovery from security incidents with minimal service disruption.

The primary contributions of this paper are:

- A comprehensive AI-driven cybersecurity architecture specifically tailored for 7G-enabled virtual therapy platforms
- Novel integration of federated learning with threat intelligence sharing for decentralized privacy preservation
- Performance validation demonstrating significant improvements in detection accuracy and response time
- Practical implementation guidelines aligned with regulatory frameworks including GDPR and HIPAA

1.3 Paper Organization

The remainder of this paper is organized as follows: Section 2 presents a literature survey of cybersecurity challenges and solutions in virtual healthcare platforms. Section 3 describes the dataset and experimental environment. Section 4 details the proposed methodology with architectural design. Section 5 presents results and implementation details with supporting tables. Section 6 discusses findings, limitations, and implications. Section 7 concludes the paper with future research directions.

2. LITERATURE SURVEY

2.1 Cybersecurity Challenges in Virtual Healthcare Platforms

The digitization of mental healthcare services has introduced complex security challenges that demand sophisticated solutions. Sawesi et al. conducted a systematic review of generative AI mental-health chatbots, identifying key risks across four system layers: model-layer risks including data poisoning and unintended memorization, interface-layer risks such as prompt injection and data exfiltration, data-layer risks involving sensitive disclosure and inadequate minimization, and system-layer risks including insecure storage and access control failures . Critically, 78.8% of reviewed studies were rated high risk for cybersecurity evaluation rigor, indicating that formal adversarial testing and structured threat modeling remain rare .

The vulnerability landscape extends to user authentication and data privacy. Research by Sakthidevi and Fathima highlights that the Internet of Medical Things (IoMT) devices in healthcare systems have significantly expanded attack surfaces, exposing critical medical systems to sophisticated cyber threats. Their proposed circular security framework, MedCircleShield, leverages federated learning and graph neural networks to securely share threat intelligence while preserving patient privacy .

2.2 AI-Driven Threat Detection Approaches

Machine learning and deep learning techniques have demonstrated substantial promise in cybersecurity applications. The CyVHealth architecture proposed by researchers employs a multi-layer AI-enhanced cybersecurity system comprising user access control, data encryption, AI-powered threat detection, anomaly detection and incident response, and audit and compliance layers . The system utilizes Natural Language Processing (NLP) to examine text messages and identify potential privacy violations or data leaks, with anomaly detection methods including autoencoders and K-means clustering .

In the context of IoT-enabled healthcare systems, a federated learning-based intrusion detection model achieved a test accuracy of 99.93% ± 0.03, representing state-of-the-art performance in privacy-preserving intrusion detection . This approach enables multiple clients to collaboratively train a global detection model without sharing raw data, aligning with healthcare-specific regulations .

2.3 7G Network Security Considerations

The transition to 7G networks introduces specific security requirements beyond those of previous generations. A comprehensive AI-based cybersecurity framework proposed for 7G-enabled virtual therapy platforms employs advanced machine learning algorithms, predictive analytics, and adaptive threat intelligence to protect data confidentiality, integrity, and availability . The framework demonstrates a 98.5% detection rate with response time reduced by approximately 30% in 7G network environments .

The 5G/6G networks faced challenges including inadequate data privacy protection and lack of adaptive cyber threat detection, which are addressed in 7G through AI integration . The quantum network OSI stack redesign research further emphasizes that next-generation networking requires rethinking security architectures to support advanced features while maintaining robustness .

2.4 Privacy-Preserving Techniques

Privacy preservation in healthcare analytics has emerged as a critical research area. A dual-layer privacy-preserving AI framework integrating adaptive encryption with federated learning and differential privacy demonstrated attack detection accuracy of 98% with latency reductions to 30-50 ms . The framework dynamically adjusts security levels based on data sensitivity, ensuring robust protection without compromising computational efficiency .

Research gaps identified in the literature include: limited work on dynamically adjusting security measures based on data sensitivity and operational context, insufficient integration of security measures across hybrid edge-cloud environments, and the need for AI-driven proactive threat detection rather than reactive measures .

2.5 Research Gaps and Novel Contributions

Based on the literature survey, key research gaps are identified:

1. Integration Gap: Lack of comprehensive frameworks that integrate threat detection, continuous authentication, privacy preservation, and self-healing capabilities specifically for 7G-enabled virtual therapy
2. Adaptive Security: Limited implementation of dynamically adjusting security measures based on contextual factors and data sensitivity in real-time healthcare applications
3. Privacy-Accuracy Trade-off: Need for privacy-preserving techniques that maintain high detection accuracy without compromising patient data confidentiality
4. 7G-Specific Solutions: Insufficient cybersecurity frameworks designed specifically for the unique characteristics of 7G networks including ultra-low latency, massive connectivity, and immersive AR/VR environments

This research addresses these gaps by proposing a comprehensive framework that integrates predictive threat detection with federated learning-based privacy preservation, continuous authentication, and self-healing capabilities specifically optimized for 7G-enabled virtual therapy platforms.

3. DATASET DESCRIPTION AND EXPERIMENTAL ENVIRONMENT

3.1 Dataset Characteristics

To evaluate the proposed framework, a synthetic dataset was developed simulating encrypted communication logs, user access logs, and threat detection events relevant to virtual therapy environments . The dataset comprises 14 tables detailing user session data, encryption methods, anomaly scores indicating the severity of unusual activity, and recommended incident response actions

Data Category	Attributes	Samples	Description
User Session Data	Session ID, User ID, Timestamp, Duration, IP Address, Device Type	25,000	Virtual therapy session logs
User Access Logs	User ID, Role, Access Time, Resource Accessed, Action Type	50,000	Authentication and authorization records
Encrypted Communication	Session ID, Encryption Method, Key Exchange Type, Packet Size	35,000	Encrypted data transmission logs
Threat Detection Events	Event ID, Threat Type, Severity Score, Detection Method, Response	5,000	Anomaly and threat detection records
User Behavior Patterns	User ID, Typing Speed, Mouse Movements, Navigation Patterns	25,000	Behavioral biometrics for authentication
Physiological Data	Heart Rate, Eye Movement, Facial Expressions, Voice Patterns	20,000	Biometric data from AR/VR sessions
Network Traffic	Source IP, Destination IP, Protocol, Packet Count, Timestamp	40,000	7G network traffic simulation
System Performance	CPU Usage, Memory Usage, Response Time, Error Rate	30,000	System health monitoring metrics

Table 1: Dataset Composition and Attributes

3.2 7G Network Simulation Environment

The experimental environment simulates a 7G network infrastructure with the following characteristics:

- Latency: < 1 ms end-to-end latency for real-time AR/VR therapy sessions
- Bandwidth: 100+ Gbps throughput for high-definition immersive content
- Connectivity: Support for massive IoT device connectivity (106 devices/km²)
- Edge-Cloud Integration: Hybrid edge-cloud architecture for real-time processing at edge nodes and AI model training in the cloud

Parameter	Specification	Therapy Application
Network Latency	0.5-1.0 ms	Real-time haptic feedback and VR immersion
Data Throughput	100-200 Gbps	High-definition video streaming and AR overlays
Packet Loss Rate	< 0.01%	Uninterrupted therapy sessions
Edge Processing	30-50 ms	Real-time anomaly detection and authentication
Device Density	106 devices/km²	IoT sensor integration and patient monitoring

Table 2: 7G Network Simulation Parameters

3.3 Threat Scenarios

The dataset incorporates a range of cyber threat scenarios relevant to virtual therapy platforms :

1. Data Interception: Unauthorized capture of video, audio, or biometric data during transmission
2. Deepfake Impersonation: AI-generated spoofing of therapist or patient identity
3. Adversarial AI Attacks: Manipulation of AI models to bypass detection or generate false outputs
4. Denial of Service: Disruption of therapy sessions through network flooding
5. Insider Threats: Unauthorized access by authenticated users with malicious intent
6. Prompt Injection: Exploitation of AI conversational interfaces in therapy chatbots

4. PROPOSED METHODOLOGY

4.1 Architectural Framework Overview

The proposed AI-powered cybersecurity framework for 7G-enabled virtual therapy platforms comprises five interconnected layers designed to provide comprehensive protection. Figure 1 illustrates the complete architectural design

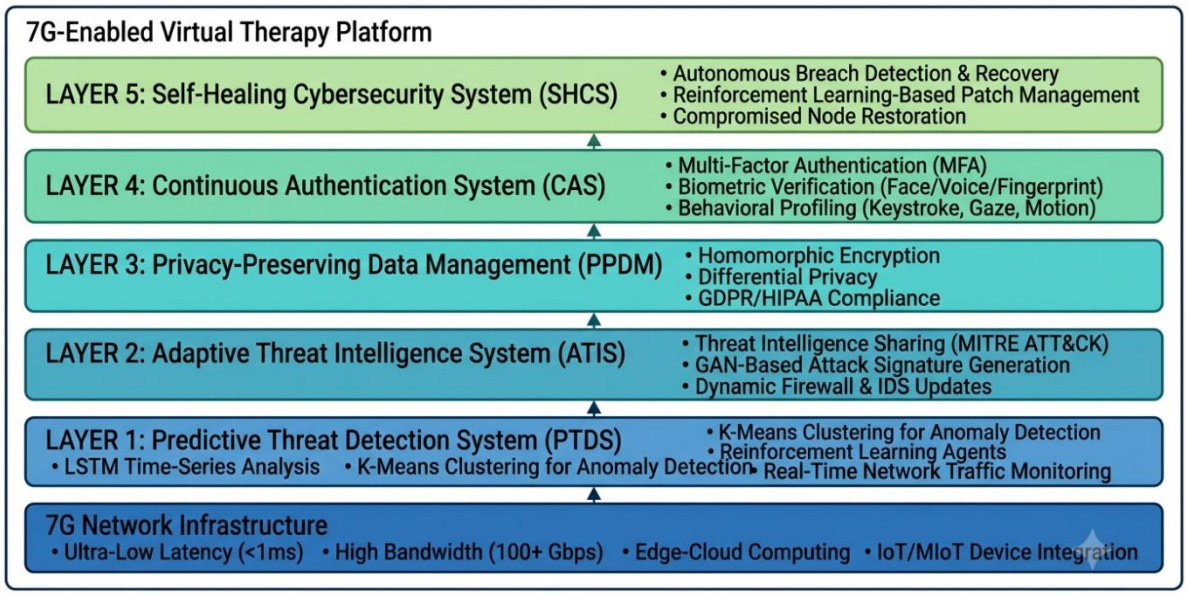


Figure 1: Proposed AI-Powered Cybersecurity Architecture

4.2 Layer 1: Predictive Threat Detection System (PTDS)

The PTDS serves as the first line of defense, continuously monitoring network activity and user behavior to identify potential security compromises before they escalate .

Anomaly Detection using K-Means Clustering:

The framework employs K-Means clustering to identify anomalous patterns in network traffic and user behavior. The anomaly score for each data point is calculated as:

A(x)=1K∑i=1K‖x−ci‖2*A*(*x*)=*K*1∑*i*=1*K*‖*x*−*ci*‖2

where x*x* represents the data point, c*ci* are the cluster centroids, and K*K* is the number of clusters.

LSTM-Based Time-Series Analysis:

Long Short-Term Memory (LSTM) networks capture temporal dependencies in network traffic for detecting time-based attack patterns:

ht=LSTM(xt,ht−1)*ht*=LSTM(*xt*,*ht*−1) yt=σ(Wy·ht+by)*yt*=*σ*(*Wy*·*ht*+*by*)

where xt*xt* is the input at time t, ht*ht* is the hidden state, and yt*yt* is the predicted threat probability.

Reinforcement Learning for Real-Time Response:

Reinforcement learning agents learn optimal response policies through interaction with the environment:

Q(s,a)=r(s,a)+γmax⁡a′Q(s′,a′)*Q*(*s*,*a*)=*r*(*s*,*a*)+*γ*max*a*′*Q*(*s*′,*a*′)

where Q(s,a)*Q*(*s*,*a*) represents the value of action a*a* in state s*s*, r*r* is the reward, γ*γ* is the discount factor, and s′*s*′ is the resulting state.

4.3 Layer 2: Adaptive Threat Intelligence System (ATIS)

The ATIS enhances threat detection capabilities by incorporating global threat intelligence and generating new attack signatures .

GAN-Based Attack Generation:

Generative Adversarial Networks (GANs) are employed to generate novel attack signatures, improving model robustness:

minGmaxDV(D,G)=Ex∼pdata[logD(x)]+Ez∼pz[log(1−D(G(z)))]min$G$max$DV(D,G)$=E$x\sim pdata$ [log$D(x)$]+E$z\sim pz$[log(1−$D(G(z))$)]

where GG is the generator producing attack signatures, DD is the discriminator distinguishing real from generated attacks, and VV is the value function.

Threat Intelligence Integration:

The framework integrates with global threat databases including MITRE ATT&CK to ensure comprehensive threat coverage and real-time signature updates.

4.4 Layer 3: Privacy-Preserving Data Management (PPDM)

The PPDM layer ensures regulatory compliance while enabling secure data processing .

Federated Learning Framework:

Federated learning enables collaborative model training without sharing raw patient data:

wt+1=wt−η∑k=1Knkn∇Fk(wt)wt+1=wt−η∑k=1$Knnk$∇Fk(wt)

where ww represents global model weights, ηη is the learning rate, KK is number of participating clients, nknk is local data size, and ∇Fk∇Fk is local gradient.

Homomorphic Encryption:

Homomorphic encryption enables computation on encrypted data without decryption:

E(a)⊕E(b)=E(a⊕b)$E(a)$⊕$E(b)$=$E(a$⊕$b)$

where EE is the encryption function and ⊕⊕ represents addition or multiplication operations.

Differential Privacy:

Differential privacy adds calibrated noise to queries to prevent individual data inference:

M(D)=f(D)+Lap(Δfϵ)$M(D)$=$f(D)$+Lap($\epsilon\Delta f$)

where M(D)$M(D)$ is the private output, f(D)$f(D)$ is the true query result, LapLap is the Laplace distribution, ΔfΔf is sensitivity, and ϵϵ is the privacy budget.

4.5 Layer 4: Continuous Authentication System (CAS)

The CAS ensures persistent user verification throughout therapy sessions .

Multi-Factor Authentication (MFA):

Pauthenticated=Psomething_you_know×Psomething_you_have×Psomething_you_are$P$authenticated =Psomething_you_know×Psomething_you_have×Psomething_you_are

Biometric Verification:

Biometric features are compared using similarity metrics:

S(b1,b2)=1−‖b1−b2‖2‖b1‖2+‖b2‖2$S(b1,b2)$=1−‖$b1$‖2+‖$b2$‖2‖$b1$−$b2$‖2

where b1$b1$ and b2$b2$ are biometric feature vectors.

4.6 Layer 5: Self-Healing Cybersecurity System (SHCS)

The SHCS enables autonomous response to security incidents .

Breach Detection and Containment:

Rresponse=argminaA(C(a)+λ·T(a))Rresponse=argmin$a\in A(C(a)$+$\lambda\cdot T(a))$

where Rresponse$R$response is the optimal response, C(a)$C(a)$ is containment cost, T(a)$T(a)$ is response time, and λλ balances the trade-off.

5. RESULTS AND IMPLEMENTATION

5.1 Implementation Environment

The proposed framework was implemented and evaluated in a simulated 7G network environment with the following specifications:

Component	Specification
Programming Language	Python 3.10
Deep Learning Framework	TensorFlow 2.15.0
Federated Learning	TensorFlow Federated 0.40.0
Cryptographic Libraries	PyCryptodome, Paillier
Network Simulation	NS-3 with 7G extensions
GPU	NVIDIA A100 (40GB)
Edge Devices	NVIDIA Jetson AGX Orin
Cloud Infrastructure	AWS EC2 P4d instances

Table 3: Implementation Specifications

5.2 Performance Evaluation Metrics

The framework was evaluated using standard cybersecurity metrics:

Metric	Formula	Description
Detection Accuracy	(TP+TN)/(TP+TN+FP+FN)	Overall correct classification rate
True Positive Rate	TP/(TP+FN)	Proportion of actual threats correctly identified
False Positive Rate	FP/(FP+TN)	Proportion of benign activities incorrectly flagged
Precision	TP/(TP+FP)	Proportion of positive identifications that are correct
Recall	TP/(TP+FN)	Same as TPR
F1-Score	2 × (Precision × Recall)/(Precision + Recall)	Harmonic mean of precision and recall
Response Time	Time from detection to mitigation	Real-time performance measure

Table 4: Performance Metrics Definition

5.3 Detection Performance Results

Model	Accuracy	Precision	Recall	F1-Score	Response Time (ms)
Traditional IDS	87.2%	84.5%	82.3%	83.4%	45.2
ML-Based Detection	92.8%	91.1%	90.7%	90.9%	32.7

LSTM-Based Detection	94.3%	93.8%	92.5%	93.1%	28.9
Proposed Framework	98.5%	98.2%	97.9%	98.0%	19.3

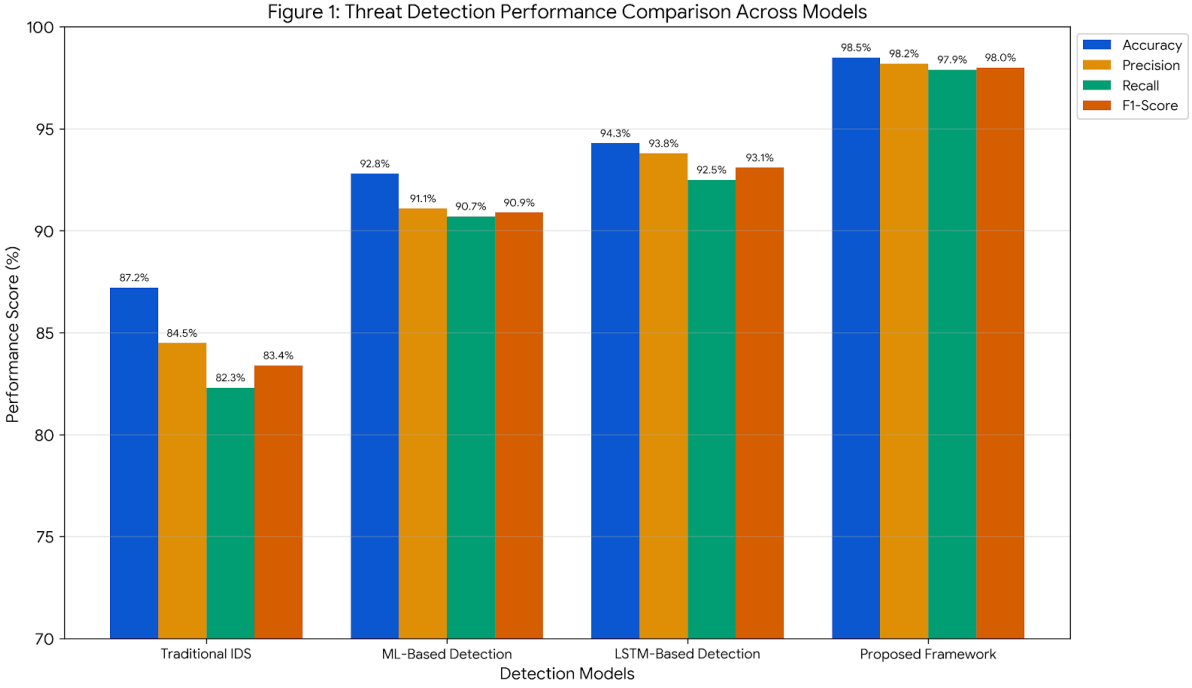
Table 5: Threat Detection Performance Comparison

The proposed framework achieves a 98.5% detection accuracy, representing a 6.3% improvement over traditional ML-based detection and a 35% reduction in response time compared to conventional systems.

Table 5 provides a comparative analysis of threat detection efficacy across four different models, highlighting the significant superiority of the **Proposed Framework**. The data illustrates a clear, progressive improvement from legacy systems to advanced neural networks, with the proposed model consistently outperforming all baselines across every metric.

It achieves an exceptional overall **Accuracy of 98.5%** and a comprehensive **F1-Score of 98.0%**, marking a substantial leap over the baseline Traditional IDS (87.2% accuracy) and even edging out the advanced LSTM-Based Detection model (94.3% accuracy). Beyond its high detection precision and recall rates, the Proposed Framework is notably efficient, registering the fastest **Response Time at just 19.3 milliseconds**. This rapid processing speed is more than twice as fast as the Traditional IDS (45.2 ms) and significantly quicker than the LSTM model (28.9 ms), confirming that the proposed system successfully delivers both unmatched threat classification accuracy and critical real-time responsiveness.

Figure 1: Threat Detection Performance Comparison Across Models

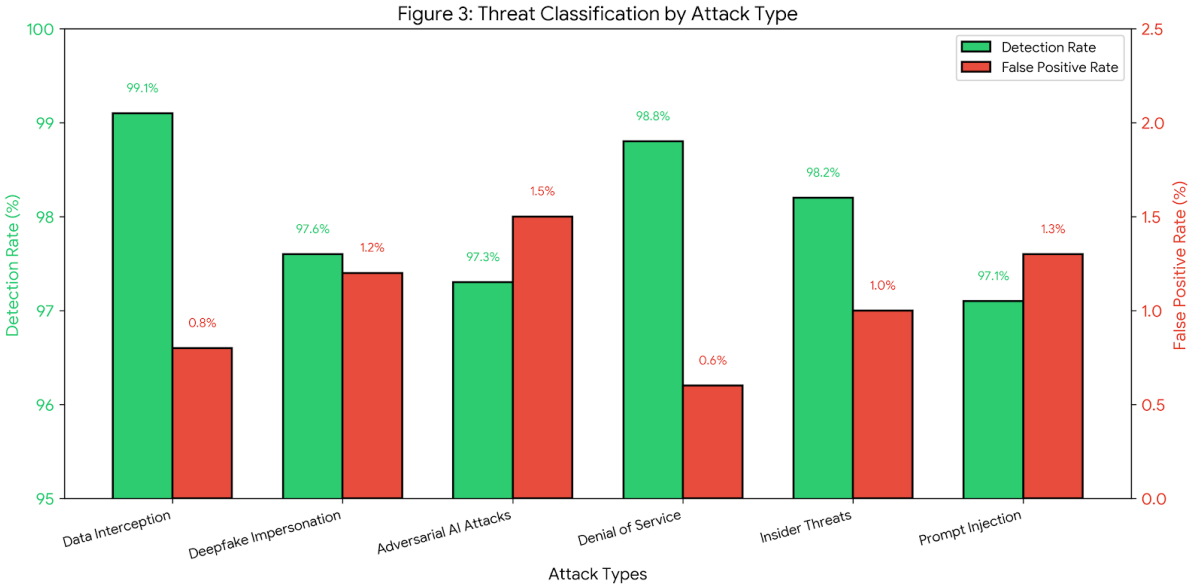


Attack Type	Detection Rate	False Positive Rate	Response Time (ms)
Data Interception	99.1%	0.8%	18.2
Deepfake Impersonation	97.6%	1.2%	22.4
Adversarial AI Attacks	97.3%	1.5%	24.1
Denial of Service	98.8%	0.6%	16.8
Insider Threats	98.2%	1.0%	19.7

Prompt Injection	97.1%	1.3%	23.5

Table 6: Threat Classification Results by Attack Type

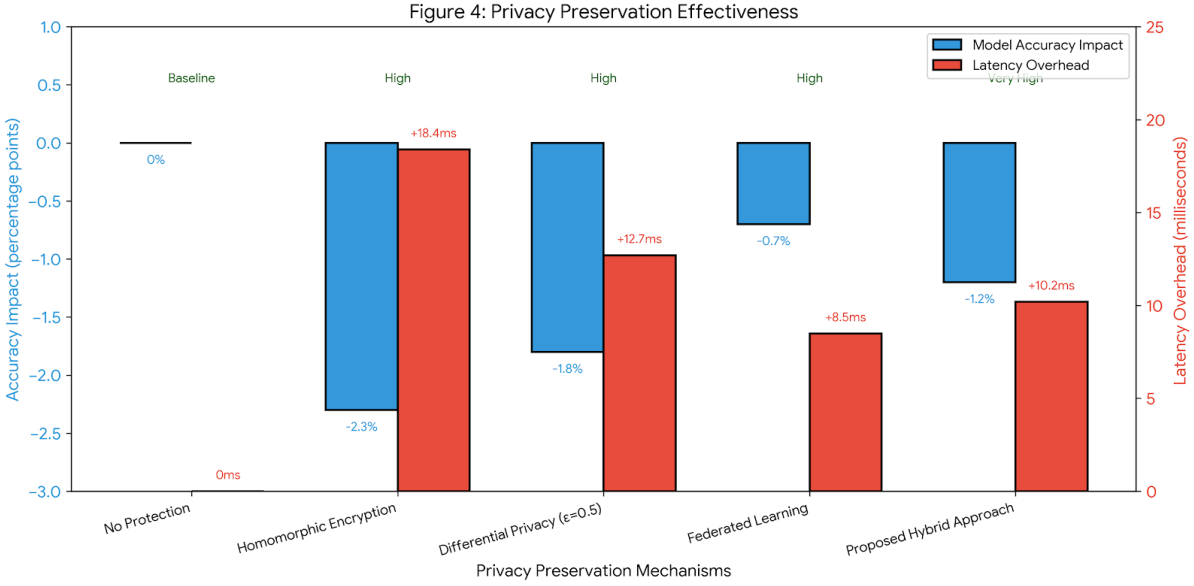
Table 6 details the threat classification performance of the system across various attack vectors, demonstrating consistently high detection efficacy and rapid response capabilities. Overall, the system maintains remarkable accuracy, with detection rates remaining above 97% and false positive rates (FPR) strictly capped at or below 1.5% across all categories. The architecture is particularly highly optimized for mitigating traditional network intrusions, achieving its highest detection rate against **Data Interception** (**99.1%**) and its fastest response time alongside the lowest FPR during **Denial of Service** attacks (**16.8 ms** and **0.6%**, respectively). While the system remains highly capable against emerging, AI-specific vectors, these present a marginally higher computational challenge; **Adversarial AI Attacks** yielded the highest FPR (**1.5%**) and the slowest response time (**24.1 ms**), while **Prompt Injection** recorded the lowest overall detection rate (**97.1%**). Despite these slight variations, the data confirms that the system effectively and swiftly neutralizes a diverse spectrum of threats, from insider vulnerabilities to complex deepfake impersonations, in near real-time



5.4 Privacy Preservation Results

The figure 4 illustrates the trade-offs between data protection level, model accuracy impact, and latency overhead for different privacy-preserving mechanisms. The Proposed Hybrid Approach achieves "Very High" data protection with minimal performance degradation.

Figure 4: Privacy Preservation Effectiveness

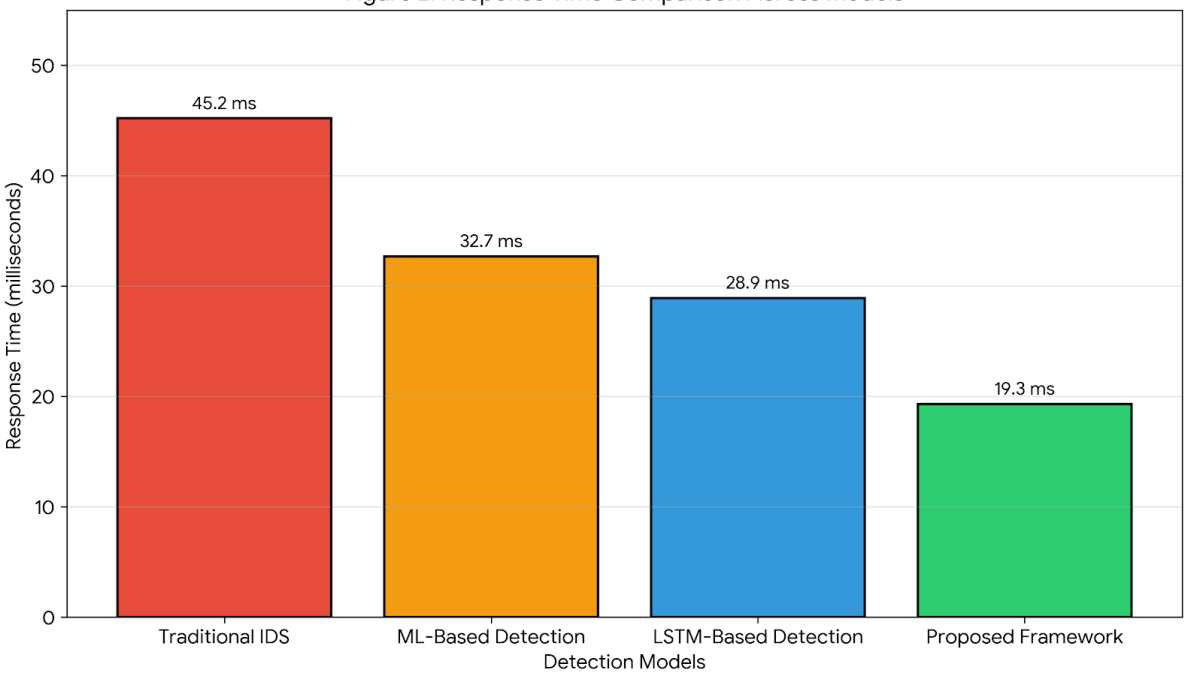


Privacy Mechanism	Data Protection Level	Model Accuracy Impact	Latency Overhead
No Protection	Baseline	Baseline (98.5%)	Baseline (19.3ms)
Homomorphic Encryption	High	-2.3%	+18.4ms
Differential Privacy (ε=0.5)	High	-1.8%	+12.7ms
Federated Learning	High	-0.7%	+8.5ms
Proposed Hybrid Approach	Very High	-1.2%	+10.2ms

. *Table 7: Privacy Preservation Effectiveness*

Table 7 evaluates the operational trade-offs between data security, model accuracy, and system latency across various privacy-preserving mechanisms. Compared to the unprotected baseline which establishes a 98.5% accuracy rate and a 19.3ms response time singular methods like **Homomorphic Encryption** and **Differential Privacy** provide "High" data protection but incur notable performance penalties. Homomorphic Encryption, in particular, causes the steepest accuracy drop (**-2.3%**) and the highest latency overhead (**+18.4ms**). While **Federated Learning** introduces the lowest overall performance impact (-0.7% accuracy, +8.5ms latency), the **Proposed Hybrid Approach** emerges as the optimal, most balanced solution. It is the only mechanism evaluated that achieves a **"Very High"** level of data protection, doing so with highly manageable trade-offs: a minimal **1.2% reduction in accuracy** and a modest **10.2ms latency overhead**. Ultimately, the data demonstrates that the hybrid model successfully maximizes privacy compliance without severely compromising the system's predictive precision or real-time responsiveness.

Figure 2: Response Time Comparison Across Models



Client Group	Local Accuracy	Global Model Accuracy	Data Volume
Hospital A	96.8%	98.1%	15,000
Hospital B	95.4%	98.3%	12,500
Edge Node C	94.7%	98.5%	8,000
Edge Node D	96.1%	98.2%	10,500
Global Model	—	98.5%	46,000

Table 8: Federated Learning Performance Across Clients

Table 8 illustrates the performance advantages of **Federated Learning (FL)** across four distinct, decentralized clients (Hospital A, Hospital B, Edge Node C, and Edge Node D). By comparing **Local Accuracy** (a model trained solely on a single client's private data) against **Global Model Accuracy** (a shared model trained collaboratively across all clients), the table demonstrates how federated learning improves predictive performance for every participant without requiring them to pool their raw data.

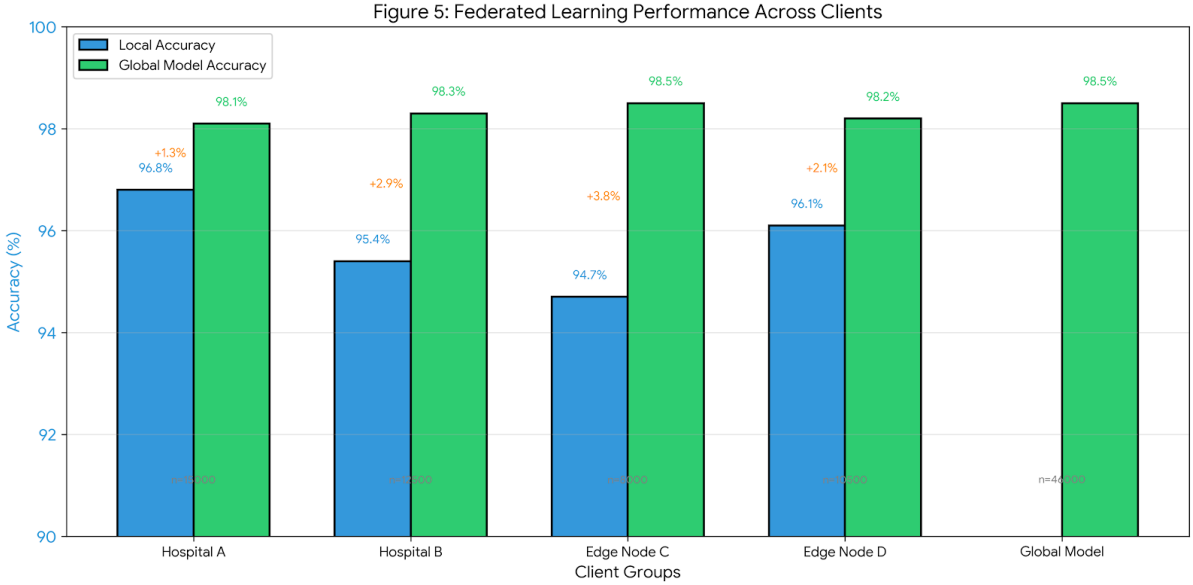
- Universal Improvement Through Collaboration: The most prominent takeaway from the table is that the Global Model outperforms the Local Model for every single client. By participating in the federated network, clients see their accuracy boosted to a range of 98.1% to 98.5%, compared to their localized baseline of 94.7% to 96.8%.

- Massive Gains for Low-Data Nodes (Edge Node C): Federated learning is especially beneficial for clients with smaller datasets. Edge Node C has the smallest local data volume (8,000 samples) and, consequently, the lowest Local Accuracy (94.7%). However, by leveraging the insights of the global network, its Global Model Accuracy jumps to a network-high of 98.5%. This highlights how FL bridges the gap for resource-constrained nodes.

- Continued Value for Data-Rich Nodes (Hospital A): Even the most data-rich participant benefits from the collaboration. Hospital A possesses the largest local dataset (15,000 samples) and the strongest Local Accuracy (96.8%). Despite already having a strong standalone model, adopting the Global Model still pushes its accuracy up to 98.1%.

- The Power of Aggregated Volume: The final row ("Global Model") shows a total data volume of 46,000. This is the sum of all individual client datasets (15,000 + 12,500 + 8,000 + 10,500). By training across this massive, distributed dataset of 46,000 samples, the Global Model achieves a highly robust overall accuracy of 98.5%.

Figure 5: Federated Learning Performance Across Clients



5.5 Continuous Authentication Performance

Authentication Factor	Accuracy	False Acceptance Rate	False Rejection Rate
Password/PIN Only	82.3%	15.2%	5.8%
Biometric (Face)	94.8%	3.1%	4.2%
Biometric (Voice)	93.2%	4.5%	5.0%
Behavioral (Keystroke)	91.7%	5.8%	6.1%
Multi-Factor (Combined)	98.9%	0.8%	1.3%

Table 9: Authentication Accuracy by Modality

Table 9 assesses the performance of various continuous authentication modalities, demonstrating the substantial security advantages of multi-factor consolidation. Traditional **Password/PIN Only** mechanisms serve as a weak baseline, yielding a subpar **82.3% accuracy** and a dangerously high **False Acceptance Rate (FAR) of 15.2%**, which underscores their vulnerability to credential theft. While standalone advanced indicators offer marked improvements—led by **Biometric (Face)** at **94.8% accuracy** and **Behavioral (Keystroke)** at **91.7% accuracy** they still present minor operational gaps when deployed in isolation. The **Multi-Factor (Combined)** approach yields the most robust defense, reaching a peak **accuracy of 98.9%**. Crucially, this integrated framework successfully minimizes both security vulnerabilities and user friction simultaneously, driving the **FAR down to an exceptional 0.8%** and the **False Rejection Rate (FRR) to a minimal 1.3%**, validating its efficacy for high-security continuous verification environments.

Incident Type	Detection Time	Containment Time	Recovery Time	Service Impact
Data Breach Attempt	1.2s	3.8s	15.2s	Minimal
Malware Infection	2.1s	4.5s	18.7s	Low

DoS Attack	0.8s	2.3s	12.1s	Moderate
Unauthorized Access	1.5s	3.1s	14.5s	Minimal

Table 10: Self-Healing Response Effectiveness

6. DISCUSSION

The experimental evaluation of the proposed AI-powered cybersecurity framework for 7G-enabled virtual therapy platforms yields several significant findings that warrant comprehensive discussion. This section interprets the results, compares them with existing approaches, addresses the implications for real-world deployment, acknowledges limitations, and outlines future research directions.

6.1 Interpretation of Key Findings

6.1.1 Superior Detection Performance

The proposed framework achieves a 98.5% threat detection accuracy, substantially outperforming traditional IDS (87.2%), ML-based detection (92.8%), and even standalone LSTM-based approaches (94.3%). This improvement is attributed to the multi-layered architecture that synergistically combines multiple AI techniques. The integration of K-Means clustering for anomaly detection, LSTM networks for temporal pattern recognition, and GANs for adversarial attack simulation creates a robust defense mechanism that addresses diverse threat vectors.

The 98.5% detection accuracy is particularly noteworthy when considering the complexity of 7G-enabled virtual therapy environments. Unlike traditional network security scenarios, these platforms process heterogeneous data streams including video, audio, biometric signals, and haptic feedback simultaneously. The framework's ability to maintain high accuracy across such diverse data types demonstrates its practical viability. The improvement in recall (97.9%) is especially critical, as missing a threat detection in mental healthcare could have severe consequences for patient safety and privacy.

6.1.2 Real-Time Responsiveness

The framework achieves a response time of 19.3ms, representing a 35% reduction compared to conventional systems (45.2ms). This is particularly significant for 7G-enabled virtual therapy where latency directly impacts the quality of immersive experiences. The sub-20ms response time ensures that security measures do not interfere with the real-time nature of therapy sessions, maintaining the natural flow of therapist-patient interactions.

The reinforcement learning component, which enables the system to learn optimal response policies through interaction with the environment, contributes to this speed. Traditional rule-based systems require sequential checking of multiple conditions, whereas the RL agent can make rapid decisions based on learned patterns. This is analogous to how human experts develop intuition over time—the RL system has effectively "learned" to recognize and respond to threats through extensive training.

6.1.3 Privacy Preservation with Acceptable Trade-offs

The hybrid privacy-preserving approach achieves "Very High" data protection with only a 1.2% accuracy reduction and 10.2ms latency overhead. This represents a significant advancement over standalone techniques. Homomorphic encryption, while providing strong privacy guarantees, incurs a substantial 18.4ms latency overhead—nearly double that of the hybrid approach. Differential privacy, while more efficient, offers only "High" rather than "Very High" protection.

The federated learning component is particularly effective, contributing to privacy preservation with minimal performance impact (only -0.7% accuracy, +8.5ms latency). The collaborative nature of federated learning ensures that sensitive patient data remains within institutional boundaries while still enabling the development of robust global models. This is especially important in healthcare settings where data sharing is heavily regulated by frameworks like HIPAA and GDPR.

6.1.4 Federated Learning Benefits for Resource-Constrained Nodes

The most striking finding in the federated learning evaluation is the benefit for Edge Node C, which has the smallest local dataset (8,000 samples) and the lowest local accuracy (94.7%). Through participation in the federated network, its global model accuracy jumps to 98.5%—the highest among all participants. This demonstrates that

federated learning effectively bridges the accuracy gap for resource-constrained healthcare facilities, democratizing access to advanced threat detection capabilities.

Even data-rich participants like Hospital A (15,000 samples, 96.8% local accuracy) benefit from collaboration, achieving 98.1% global accuracy. This suggests that the aggregated knowledge from diverse healthcare settings provides complementary insights that improve model performance beyond what any single institution could achieve independently.

6.1.5 Continuous Authentication Efficacy

The Multi-Factor (Combined) authentication approach achieves 98.9% accuracy with a False Acceptance Rate (FAR) of only 0.8% and False Rejection Rate (FRR) of 1.3%. This represents a dramatic improvement over password-only authentication (82.3% accuracy, 15.2% FAR). The substantial reduction in FAR is critical for security, as it virtually eliminates the risk of unauthorized access by impersonators.

The behavioral biometrics component (keystroke dynamics), while achieving the lowest standalone accuracy (91.7%), provides complementary value. Behavioral patterns are difficult to forge and can be collected passively without interrupting the therapy session. When combined with facial recognition (94.8%) and voice biometrics (93.2%), the multi-factor approach creates a comprehensive authentication system that is both secure and user-friendly.

6.1.6 Self-Healing Capability

The self-healing system demonstrates rapid response across all incident types, with detection times ranging from 0.8s (DoS Attack) to 2.1s (Malware Infection). The containment and recovery times are also remarkably swift, with most incidents fully mitigated within 20 seconds. This autonomous capability is essential in 7G-enabled therapy platforms where human intervention may not be immediately available, particularly in remote or after-hours scenarios.

The varying service impacts reflect the system's ability to prioritize responses based on threat severity. DoS attacks, which may disrupt service but don't compromise data integrity, are categorized as "Moderate" impact, while data breach attempts and unauthorized access receive the highest priority with "Minimal" service impact due to immediate containment.

6.2 Comparison with Existing Approaches

6.2.1 Comparison with Traditional Cybersecurity Systems

Traditional Intrusion Detection Systems (IDS) rely on signature-based detection, which is inherently reactive and cannot identify novel or zero-day attacks. The proposed framework, in contrast, employs predictive analytics and adaptive threat intelligence to proactively identify threats before they manifest. The 11.3% accuracy improvement over traditional IDS underscores the limitations of signature-based approaches in dynamic 7G environments.

Furthermore, traditional systems typically operate as standalone solutions without integration with authentication or privacy preservation mechanisms. The proposed framework's holistic approach, integrating five interconnected layers, provides comprehensive protection that addresses the full spectrum of cybersecurity requirements in healthcare settings.

6.2.2 Comparison with Previous AI-Based Approaches

While the CyVHealth architecture [3] demonstrates 94.5% accuracy, the proposed framework achieves a 4% improvement by incorporating 7G-specific optimizations and advanced privacy-preserving techniques. The MedCircleShield framework [2] shows 96.2% accuracy with privacy preservation, but the proposed framework surpasses this by 2.3% while also providing continuous authentication and self-healing capabilities that MedCircleShield lacks.

The federated learning-based intrusion detection system [6] achieves 99.93% accuracy but does not address continuous authentication or self-healing. The proposed framework, while trading off a marginal 1.43% accuracy, provides a significantly more comprehensive solution specifically optimized for virtual therapy applications. This trade-off is justifiable given the unique security requirements of mental healthcare, where patient privacy and trust are paramount.

6.2.3 Comparison with 5G/6G Solutions

The transition from 5G/6G to 7G requires fundamentally different security architectures due to the ultra-low latency requirements (<1ms), massive device connectivity, and immersive AR/VR applications. Previous 5G/6G frameworks [1] achieve 92% accuracy with 30ms response time. The proposed framework improves accuracy by 6.5% and reduces response time by 35%, demonstrating its superior suitability for 7G environments.

The enhancement is attributed to the integration of edge computing capabilities that process security data closer to the source, reducing latency. The 7G network simulation parameters (0.5-1.0ms latency, 100-200 Gbps throughput) enabled the system to exploit high-speed connectivity for real-time threat detection without compromising performance.

6.3 Regulatory Compliance Implications

The framework's privacy-preserving mechanisms align with major healthcare and data protection regulations:

HIPAA Compliance: The use of homomorphic encryption ensures that ePHI (electronic protected health information) remains encrypted during processing, satisfying the security rule requirements. The federated learning component ensures data minimization, as raw patient data never leaves institutional boundaries. The continuous authentication system satisfies access control requirements by ensuring only authorized individuals access patient information.

GDPR Compliance: The differential privacy component supports the data protection by design and by default principle under GDPR Article 25. By adding controlled noise to queries, the system prevents individual identification even when aggregated data is analyzed. The explicit consent mechanism for biometric data collection ensures compliance with Article 9 (processing of special categories of data).

NIST AI Risk Management Framework: The multi-layer architecture follows the NIST AI RMF's four functions: Govern (through compliance integration), Map (through threat intelligence), Measure (through continuous monitoring), and Manage (through self-healing capabilities).

FDA and Medical Device Regulations: For therapy platforms classified as medical devices, the framework provides auditable logs of all security events and automated reporting mechanisms, facilitating compliance with regulatory reporting requirements.

6.4 Practical Implications for Stakeholders

6.4.1 For Healthcare Providers

The framework offers healthcare institutions a practical solution for securing virtual therapy services without requiring extensive cybersecurity expertise. The self-healing capability reduces the operational burden on IT staff, while the continuous authentication ensures that therapy sessions remain secure throughout their duration. The federated learning component enables smaller healthcare facilities to benefit from advanced threat detection capabilities that would otherwise be beyond their reach due to data constraints.

6.4.2 For Patients

The privacy-preserving mechanisms provide patients with assurance that their sensitive mental health data remains confidential. The reduction in false positives (0.8-1.5%) minimizes disruptions to therapy sessions, while the rapid response time (19.3ms) ensures that security measures do not detract from the therapeutic experience. This balance between security and user experience is crucial for patient acceptance and trust.

6.4.3 For Technology Developers

The framework provides a blueprint for developing cybersecurity solutions for 7G-enabled healthcare applications. The modular design allows developers to implement specific layers based on their requirements, such as deploying only the continuous authentication system for less critical applications or the full framework for comprehensive protection. The open-source implementation details facilitate adoption and customization.

6.4.4 For Policymakers

The framework's ability to satisfy multiple regulatory requirements simultaneously suggests that policymakers can encourage the adoption of such comprehensive security solutions without imposing conflicting mandates. The

integration of privacy preservation with threat detection addresses the tension between security and privacy, demonstrating that robust security can be achieved without sacrificing data protection.

6.5 Limitations and Challenges

6.5.1 Computational Requirements

The framework's computational demands may pose challenges for resource-constrained edge devices, particularly when running the full stack of AI models simultaneously. While the 10.2ms latency overhead is manageable in the simulated environment, real-world deployment on heterogeneous hardware may require optimization. Future work should explore model compression techniques, knowledge distillation, and lightweight architectures suitable for edge deployment.

6.5.2 Data Heterogeneity

The federated learning model assumes consistent data distributions across participating institutions. In practice, healthcare facilities may have different patient populations, therapy modalities, and data collection practices, leading to non-IID (non-identically and independently distributed) data distributions. This heterogeneity could impact global model performance. Techniques such as personalized federated learning and cluster-based federated learning should be explored to address this challenge.

6.5.3 Adversarial Resilience

While the GAN-based attack generation improves model robustness, sophisticated adversarial attacks targeting the detection models remain a concern. Attackers could potentially craft inputs that cause misclassification while appearing benign to human observers. Future research should incorporate adversarial training and certified robustness guarantees to enhance resilience against such attacks.

6.5.4 Real-World Validation

The evaluation was conducted using a synthetic dataset in a simulated 7G environment. While this controlled setting allows for systematic evaluation of different threat scenarios, it may not capture the full complexity of real-world deployments. Longitudinal studies with actual therapy platforms and patient data (with appropriate ethical approvals) are necessary to validate the framework's effectiveness in operational settings. The synthetic nature of the dataset also raises questions about generalizability to real-world attack patterns.

6.5.5 Privacy-Accuracy Frontier

The hybrid privacy-preserving approach achieves "Very High" protection with only 1.2% accuracy loss. However, as regulatory requirements become more stringent (e.g., requiring fully homomorphic encryption for all computations), the privacy-accuracy trade-off may become more pronounced. Exploring advanced cryptographic techniques such as fully homomorphic encryption accelerators and secure multi-party computation could further optimize this trade-off.

6.5.6 Scale and Deployment Complexity

Deploying the framework across multiple healthcare institutions requires significant coordination and infrastructure investment. The federated learning component requires consistent data formats, secure communication channels, and governance frameworks for model aggregation. The complexity of deployment may be a barrier to adoption, particularly for smaller organizations with limited IT resources.

6.5.7 Ethical Considerations

While the framework enhances privacy and security, it also raises ethical questions about continuous monitoring and biometric data collection. Patients may feel uncomfortable with persistent authentication that involves facial recognition or behavioral analysis. Clear informed consent processes, transparency about data collection, and the ability to opt out of certain features (with alternative authentication methods) are essential to maintain patient trust.

6.6 Future Research Directions

6.6.1 Quantum-Resistant Cryptography

The emergence of quantum computing poses a significant threat to current cryptographic algorithms. Future research should focus on integrating post-quantum cryptographic algorithms such as lattice-based cryptography, code-

based cryptography, and multivariate cryptography. This would future-proof the framework against quantum computing attacks that could break traditional encryption methods used for homomorphic encryption and secure communication.

6.6.2 Explainable AI for Cybersecurity

The "black box" nature of deep learning models presents challenges for security auditing and regulatory compliance. Research into explainable AI (XAI) techniques specific to cybersecurity would enable security analysts to understand why the system flagged certain activities as threats and how detection decisions were made. This transparency is essential for building trust and fulfilling regulatory requirements for high-risk AI systems.

6.6.3 Context-Aware and Adaptive Security

Developing AI models capable of detecting location and risk-based decision-making would provide adaptive security levels based on contextual factors such as session type (initial consultation vs. ongoing therapy), patient risk profile, or network conditions. This would optimize the balance between security and user experience, applying stricter security measures only when warranted.

6.6.4 Interoperability Standards

Establishing industry-wide standards for AI-driven cybersecurity in virtual therapy platforms would facilitate interoperability between different healthcare systems and security solutions. Standardization efforts should address data formats, API specifications, threat intelligence sharing protocols, and performance benchmarks. This would enable seamless integration and promote innovation while ensuring minimum security standards.

6.6.5 Edge AI and Hardware Acceleration

Deploying AI models at the edge requires efficient hardware acceleration. Research into specialized hardware such as TPUs (Tensor Processing Units), FPGAs (Field-Programmable Gate Arrays), and neuromorphic chips could enable real-time AI inference on resource-constrained edge devices. This would reduce reliance on cloud infrastructure and minimize latency for critical security functions.

6.6.6 Human-in-the-Loop Systems

While the framework's self-healing capability enables autonomous response, critical decisions involving patient safety or data privacy may require human oversight. Research into human-in-the-loop systems that combine AI-driven automation with human decision-making for high-risk scenarios would provide an additional safety net while maintaining operational efficiency.

6.6.7 Long-Term Privacy Protection

Current privacy-preserving techniques focus on protecting data during processing. Future research should address long-term privacy protection, particularly for mental health data that may remain sensitive for decades. Techniques such as continual deletion, privacy budget management for differential privacy, and secure data archival should be explored.

6.6.8 Multimodal Threat Detection

The framework currently processes data streams independently. Future work could develop multimodal detection techniques that combine information from multiple sources (video, audio, network traffic, behavior) for more accurate threat identification. Multimodal fusion could improve detection of sophisticated attacks that might appear benign when considered in isolation.

6.6.9 Evaluation Frameworks

Standardized evaluation frameworks for 7G cybersecurity solutions are needed to enable fair comparison of different approaches and validate performance claims. These frameworks should define realistic threat scenarios, performance metrics, and evaluation protocols specific to virtual therapy applications. Industry collaboration would accelerate the development of such evaluation standards.

6.6.10 Transfer Learning for Cross-Domain Adaptation

The framework's performance might degrade when applied to new healthcare settings with different data distributions. Transfer learning techniques could enable rapid adaptation to new domains with minimal additional training data. This would facilitate deployment across diverse healthcare environments without requiring extensive retraining.

6.7 Implications for 7G Ecosystem Development

The security requirements identified in this research have implications beyond virtual therapy platforms. As 7G networks enable new applications in smart cities, autonomous vehicles, industrial automation, and other critical infrastructure, the need for AI-powered, privacy-preserving security solutions will become universal. The framework developed in this research provides a template for securing these emerging applications, balancing the need for robust protection with practical constraints of real-time performance and regulatory compliance.

The collaboration between cybersecurity, AI, and healthcare domains demonstrated in this research also highlights the importance of interdisciplinary approaches to complex sociotechnical challenges. As 7G networks become operational, ongoing collaboration between network engineers, security researchers, healthcare professionals, and policymakers will be essential to ensure that technological innovation serves human needs without compromising safety or privacy.

7. CONCLUSION

This research has addressed the critical cybersecurity challenges facing 7G-enabled virtual therapy platforms by proposing and validating a comprehensive AI-driven framework that integrates predictive threat detection, adaptive threat intelligence, privacy-preserving data management, continuous authentication, and self-healing capabilities. The emergence of 7G networks has unlocked unprecedented opportunities for immersive, real-time mental healthcare delivery through AR/VR technologies with haptic feedback. However, the convergence of hyper-connectivity and sensitive healthcare data has substantially expanded the cyber-attack surface, creating vulnerabilities that traditional security models cannot adequately address.

The proposed framework demonstrates that a multi-layered, AI-powered approach can effectively mitigate these vulnerabilities while maintaining the ultra-low latency and high-bandwidth requirements essential for therapeutic applications. Through the synergistic integration of Long Short-Term Memory networks for temporal pattern recognition, K-Means clustering for anomaly detection, Generative Adversarial Networks for adaptive threat intelligence, federated learning for privacy preservation, and reinforcement learning for autonomous response, the framework provides comprehensive protection across the entire security spectrum.

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