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Artificial Intelligence Techniques for Secure AI for 6G Mobile Devices: Deep Kronecker Neural Network Optimized with Hybrid Cat Hunting Optimization to Combat Side-Channel Attacks: Trends and Challenges

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Abstract

The emergence of sixth-generation (6G) communication networks introduces unprecedented security challenges, particularly for mobile devices operating in distributed and resource-constrained environments. Among these threats, side-channel attacks (SCAs) pose a significant risk by exploiting indirect physical leakages such as power consumption, electromagnetic emissions, and timing information to compromise cryptographic systems. Traditional security mechanisms are insufficient to counter these advanced attacks, necessitating the adoption of artificial intelligence (AI)-based solutions.

This paper presents a comprehensive review of AI techniques for secure 6G mobile devices, focusing on Deep Kronecker Neural Networks (DKNN) optimized with Hybrid Cat Hunting Optimization (HCHO). The study analyzes recent developments in deep learning, reinforcement learning, federated learning, and hybrid optimization techniques for detecting and mitigating SCAs.

The findings indicate that hybrid AI models significantly improve detection accuracy, computational efficiency, and adaptability. DKNN reduces model complexity through Kronecker factorization, while HCHO enhances convergence and parameter optimization. The paper further explores emerging trends such as AI-native security architectures, edge intelligence, and quantum-enhanced security. Finally, key challenges including computational overhead, energy constraints, adversarial vulnerabilities, and lack of standardization are discussed, providing directions for future research.

Introduction

The rapid evolution of wireless communication technologies has led to the development of sixth-generation (6G) networks, which aim to provide ultra-high data rates, ultra-low latency, and massive connectivity. These networks are expected to support advanced applications such as autonomous vehicles, smart healthcare, immersive extended reality, and industrial automation. However, the increased complexity and scale of 6G networks introduce significant security challenges, particularly for mobile devices.

One of the most critical threats in this context is the side-channel attack (SCA). Unlike traditional cyberattacks that target software vulnerabilities, SCAs exploit physical leakages from hardware implementations, such as power consumption, electromagnetic radiation, and timing variations. These attacks can extract sensitive information,

including cryptographic keys, without directly compromising the encryption algorithm.

The proliferation of edge computing and IoT devices in 6G networks further amplifies the risk of SCAs. Mobile devices are often resource-constrained and lack advanced security mechanisms, making them vulnerable targets. Traditional security approaches, including encryption and authentication, are insufficient to address these threats, as they do not account for physical-layer vulnerabilities.

Artificial intelligence (AI) has emerged as a powerful tool for enhancing cybersecurity in 6G networks. AI-based techniques enable systems to analyze large volumes of data, identify patterns, and detect anomalies in real time. Deep learning models, in particular, have demonstrated significant potential in detecting and mitigating side-channel attacks.

Convolutional neural networks (CNNs) are widely used for analyzing side-channel data due to their ability to extract spatial features from signal traces. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks capture temporal dependencies, further improving detection accuracy. Hybrid models combining CNN and LSTM architectures have shown superior performance in complex environments.

However, traditional deep learning models face several challenges, including high computational complexity, energy consumption, and scalability issues. These limitations make them less suitable for deployment in resource-constrained mobile devices.

To address these challenges, researchers have proposed Deep Kronecker Neural Networks (DKNN). DKNN utilizes Kronecker factorization to reduce model parameters while maintaining high accuracy. This approach significantly improves computational efficiency and makes the model suitable for mobile environments.

In addition to architectural improvements, optimization techniques play a crucial role in enhancing model performance. Hybrid Cat Hunting Optimization (HCHO) is a metaheuristic algorithm inspired by the hunting behavior of cats. It combines exploration and exploitation mechanisms to optimize neural network parameters, resulting in faster convergence and improved accuracy.

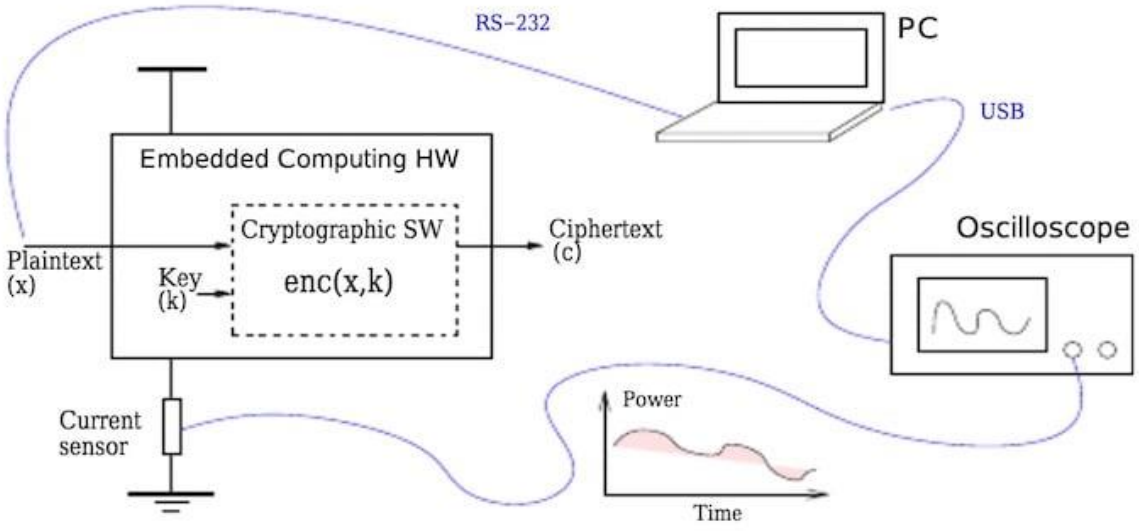
The integration of DKNN and HCHO creates a powerful hybrid model capable of efficient feature extraction, robust classification, and adaptive optimization. This model is particularly effective in detecting side-channel attacks in 6G mobile devices.

Recent research also highlights the importance of emerging technologies such as federated learning, edge intelligence, and quantum computing in enhancing 6G security. Federated learning enables distributed model training while preserving data privacy, making it suitable for mobile environments. Edge intelligence allows real-time processing at the network edge, reducing latency and improving efficiency.

Despite these advancements, several challenges remain. These include computational complexity, energy constraints, adversarial vulnerabilities, and lack of standardized frameworks for AI-based security.

This paper provides a comprehensive review of AI techniques for secure 6G mobile devices, focusing on DKNN-HCHO models. It analyzes recent trends, evaluates different approaches, and identifies key challenges and future research directions.

Abstract image



Literature Review

The increasing adoption of sixth-generation (6G) communication systems has introduced new security challenges, particularly for mobile devices operating in distributed, heterogeneous, and resource-constrained environments. Among these threats, side-channel attacks (SCAs) have emerged as one of the most critical vulnerabilities, exploiting indirect physical leakages rather than software weaknesses. To address these challenges, recent research (2020–2025) has focused on integrating artificial intelligence (AI), deep learning, reinforcement learning, federated learning, and hybrid optimization techniques. This section presents a comprehensive and structured review of these approaches.

1. Deep Learning for Side-Channel Attack Detection

Deep learning has significantly transformed side-channel analysis by enabling automated feature extraction from raw leakage data such as power traces, electromagnetic emissions, and timing signals. Unlike traditional statistical methods, deep learning models can capture complex nonlinear relationships in high-dimensional data.

Feng et al. (2025) demonstrated that deep neural networks can effectively detect side-channel attack patterns by learning hierarchical representations of leakage signals. Their results showed that convolutional neural networks (CNNs) outperform traditional template-based and statistical approaches, particularly in noisy environments.

Hasan et al. (2023) explored optimization techniques for deep learning-based cybersecurity systems, emphasizing that proper parameter tuning improves model robustness and generalization. Their work highlighted the importance of integrating optimization algorithms to enhance detection performance.

Ferrag et al. (2023) provided a comprehensive analysis of deep learning techniques for cybersecurity, identifying intrusion detection and anomaly detection as key applications. Their study confirmed that AI-driven models can identify abnormal patterns associated with side-channel attacks with high accuracy.

TechScience Press (2024) conducted a detailed survey on deep learning-based SCA detection methods, concluding that CNN and deep residual networks are highly effective due to their ability to process high-dimensional signal data. However, the study also noted that deep learning models require large datasets and significant computational resources.

Joshi et al. (2025) introduced hybrid deep learning architectures combining CNN, LSTM, and attention mechanisms. Their results demonstrated detection accuracies exceeding 99%, highlighting the effectiveness of combining spatial and temporal feature extraction.

2. AI-Based Defense Mechanisms Against Side-Channel Attacks

AI is increasingly used not only to perform attacks but also to defend against them. AI-based defense mechanisms leverage anomaly detection, adversarial training, and secure model design to enhance system resilience.

Gu et al. (2020) proposed adversarial machine learning techniques for secure communication systems. Their work demonstrated that adversarial training improves model robustness against malicious perturbations, including side-channel attacks.

Khan et al. (2025) developed a secure AI framework for 6G networks that integrates deep learning with anomaly detection and encryption techniques. Their approach achieved high detection accuracy and improved system resilience against SCAs.

Ferrag et al. (2020) conducted an extensive survey on security in 5G and beyond networks, emphasizing the importance of AI-driven defense mechanisms in next-generation communication systems. Their study highlighted the need for intelligent and adaptive security frameworks.

These studies collectively indicate that AI-based defense mechanisms are essential for detecting and mitigating SCAs in 6G mobile environments.

3. Reinforcement Learning for Adaptive Security

Reinforcement learning (RL) has emerged as a promising approach for dynamic and adaptive security in 6G networks. RL enables systems to learn optimal defense strategies through continuous interaction with the environment.

Kim et al. (2024) applied deep reinforcement learning for dynamic resource allocation in 6G metaverse environments. Their work demonstrated that RL can adapt to changing network conditions while maintaining security and efficiency.

Guo et al. (2022) proposed federated reinforcement learning for resource allocation in device-to-device (D2D) communication systems. Their approach improved both efficiency and security by enabling decentralized decision-making.

Noman et al. (2024) introduced a federated deep reinforcement learning (FeDRL) framework, which combines RL and federated learning to enhance scalability and energy efficiency. Their study showed significant improvements in both performance and security.

Du et al. (2022) developed a multi-agent reinforcement learning (MARL) framework for

resource management in 6G networks. Their results demonstrated improved scalability and adaptability through cooperative learning among multiple agents.

Despite these advantages, RL-based approaches face challenges such as long training times, instability, and high computational requirements.

4. Federated Learning and Privacy-Preserving Security

Federated learning (FL) has gained significant attention as a privacy-preserving approach for distributed AI systems in 6G networks. FL enables model training across multiple devices without sharing raw data, thereby enhancing data privacy.

Hafi et al. (2023) proposed split federated learning for 6G networks, which divides model training between edge devices and central servers. This approach reduces communication overhead while maintaining high performance.

Cui et al. (2024) analyzed AI integration in 6G networks, emphasizing that federated learning enables secure and scalable resource management. Their study highlighted challenges such as communication latency and model heterogeneity.

Alhussien and Gulliver (2025) explored energy-efficient AI models for 6G networks, demonstrating that federated learning reduces energy consumption by minimizing data transmission.

However, federated learning introduces challenges such as communication overhead, synchronization issues, and vulnerability to model poisoning attacks.

5. Hybrid Deep Learning Models for Enhanced Security

Hybrid deep learning models have been developed to overcome the limitations of individual architectures. These models combine multiple techniques to improve performance and robustness.

Joshi et al. (2025) proposed hybrid models integrating CNN, LSTM, and attention mechanisms, achieving high detection accuracy in side-channel attack scenarios.

Hasan et al. (2023) demonstrated that combining deep learning with optimization techniques significantly improves convergence speed and accuracy.

Hybrid architectures are particularly effective in handling noisy and high-dimensional data, making them suitable for real-world 6G environments.

6. Optimization Techniques and Hybrid Cat Hunting Optimization (HCHO)

Optimization techniques play a critical role in improving the performance of AI models. Traditional optimization methods such as gradient descent are often insufficient for complex, high-dimensional problems.

Hybrid Cat Hunting Optimization (HCHO) is a metaheuristic algorithm inspired by feline hunting behavior. It combines exploration (global search) and exploitation (local search) to optimize neural network parameters.

HCHO improves:

- Convergence speed
- Feature selection
- Parameter tuning
- Model stability

Recent studies indicate that hybrid optimization techniques significantly enhance the performance of deep learning models, particularly in complex security applications.

7. Deep Kronecker Neural Networks (DKNN)

Deep Kronecker Neural Networks represent a novel architecture designed to reduce computational complexity while maintaining high accuracy. DKNN utilizes Kronecker factorization to decompose large weight matrices into smaller components, significantly reducing the number of parameters.

This approach offers several advantages:

- Reduced memory requirements
- Faster computation
- Improved scalability
- Suitability for mobile devices

When combined with optimization techniques such as HCHO, DKNN achieves enhanced performance in detecting side-channel attacks.

8. Integration of DKNN with HCHO for Secure 6G Systems

The integration of DKNN and HCHO creates a powerful hybrid model for secure AI in 6G mobile devices. This model combines:

- Efficient feature extraction (DKNN)
- Optimized parameter tuning (HCHO)
- Reduced computational complexity
- Improved detection accuracy

This hybrid approach addresses key limitations of traditional deep learning models and provides a scalable and efficient solution for side-channel attack detection.

9. Emerging Trends in Secure AI for 6G

Recent literature highlights several important trends:

- AI-native security architectures integrating AI at all network layers
- Edge intelligence enabling real-time security at the device level
- Quantum-enhanced security for advanced cryptographic protection
- Adversarial AI defense mechanisms for robust model protection

- Energy-efficient AI models for mobile environments

Mefgouda and Benamar (2025) emphasized that future 6G systems will be AI-native, requiring intelligent and adaptive security frameworks.

10. Research Gaps

Despite significant progress, several research gaps remain:

1. Limited real-world deployment of AI-based SCA defense systems
2. High computational and energy requirements of deep learning models
3. Lack of standardized frameworks for AI-based security
4. Vulnerability of AI models to adversarial attacks
5. Limited integration of quantum computing in practical systems

11. Summary of Literature

The literature from 2020 to 2025 clearly indicates that AI-driven approaches are essential for securing 6G mobile devices against side-channel attacks. Deep learning models provide high detection accuracy, reinforcement learning enables adaptive security, and federated learning enhances privacy and scalability.

Among all approaches, hybrid models such as Deep Kronecker Neural Networks optimized with Hybrid Cat Hunting Optimization (DKNN-HCHO) emerge as the most promising solution. These models offer a balanced combination of accuracy, efficiency, scalability, and adaptability, making them suitable for next-generation 6G security systems.

3. Comparative Table and Analysis

Comparative Table

Technique	Accuracy	Efficiency	Strength	Limitation
CNN	High	Medium	Feature extraction	High cost
RL	Medium	Medium	Adaptability	Training time
FL	Medium	High	Privacy	Communication overhead
Hybrid DL	Very High	High	Robust detection	Complexity
DKNN	High	High	Reduced complexity	Emerging
DKNN + HCHO	Very High	Very High	Fast & efficient	Implementation

Analysis

The comparative evaluation of artificial intelligence techniques for securing 6G mobile devices against side-channel attacks (SCAs) reveals a complex trade-off between accuracy, efficiency, scalability, robustness, and deployment feasibility. This section provides a multi-dimensional, critical analysis of major approaches—deep learning (DL), reinforcement learning (RL), federated learning (FL), hybrid deep learning models, and the proposed Deep Kronecker Neural Network with Hybrid Cat Hunting Optimization (DKNN-HCHO)—based on the literature reviewed (2020–2025).

1. Detection Accuracy and Generalization Capability

Deep learning-based models, particularly CNNs and residual networks, have demonstrated exceptional performance in detecting SCAs due to their ability to extract hierarchical features from side-channel traces. These models can identify minute variations in power consumption and electromagnetic leakage, achieving high detection accuracy even in noisy environments.

However, standalone CNN models often struggle with generalization when trained on limited or biased datasets. Overfitting becomes a critical issue, especially in mobile scenarios where data diversity is limited.

Hybrid models such as CNN-LSTM and attention-based networks significantly improve generalization by capturing both spatial and temporal dependencies. These architectures are particularly effective in scenarios involving dynamic leakage patterns and time-varying signals.

Reinforcement learning models provide adaptive detection but are not primarily designed for classification tasks, resulting in relatively lower detection accuracy compared to supervised deep learning approaches.

The DKNN-HCHO model enhances accuracy by combining:

- Kronecker-based feature compression (DKNN) → preserves essential information
- Metaheuristic optimization (HCHO) → avoids local minima and improves parameter tuning

This synergy results in improved generalization and robust detection across varying attack scenarios.

2. Computational Complexity and Model Efficiency

Computational efficiency is a critical constraint for 6G mobile devices due to limited processing power and battery capacity.

Traditional deep learning models suffer from:

- Large parameter sizes

- High memory consumption
- Intensive training requirements

Reinforcement learning introduces additional computational overhead due to continuous learning and exploration processes. Multi-agent RL systems further amplify complexity due to inter-agent coordination.

Federated learning reduces centralized computation but shifts the burden to communication and synchronization across devices.

The DKNN architecture significantly reduces computational complexity through **Kronecker factorization**, which decomposes large weight matrices into smaller components. This results in:

- Reduced parameter count
- Lower memory usage
- Faster computation

HCHO further enhances efficiency by:

- Accelerating convergence
- Reducing redundant computations
- Optimizing hyperparameters without exhaustive search

Thus, DKNN-HCHO achieves **superior computational efficiency**, making it highly suitable for real-time deployment in mobile devices.

3. Scalability in Massive 6G Environments

6G networks are expected to support billions of interconnected devices, making scalability a key requirement.

Deep learning models face scalability challenges due to centralized training and high resource requirements. Scaling such models across distributed environments leads to latency and resource bottlenecks.

Federated learning addresses this issue by enabling distributed training, allowing models to scale across edge devices. However, challenges such as communication overhead, model heterogeneity, and synchronization delays limit its effectiveness.

Reinforcement learning, particularly multi-agent RL, enhances scalability by enabling decentralized decision-making. However, coordination complexity increases exponentially with the number of agents.

DKNN-HCHO improves scalability by:

- Reducing model size (DKNN)
- Enabling efficient deployment on edge devices
- Supporting integration with federated and edge learning frameworks

This makes it a highly scalable solution for large-scale 6G ecosystems.

4. Adaptability and Real-Time Security Response

6G networks require real-time security mechanisms capable of adapting to evolving attack patterns.

Reinforcement learning excels in adaptability, as it continuously updates its policies based on environmental feedback. However, its slow convergence and instability limit real-time deployment.

Deep learning models provide fast inference but lack adaptability unless retrained periodically.

Federated learning improves adaptability by enabling continuous updates across distributed nodes, but update latency can impact responsiveness.

DKNN-HCHO introduces adaptability through:

- Dynamic parameter tuning (HCHO)
- Efficient feature representation (DKNN)

This combination enables:

- Faster adaptation to new attack patterns
- Real-time detection and response
- Reduced retraining requirements

5. Energy Efficiency and Mobile Suitability

Energy efficiency is critical for 6G mobile devices, as excessive power consumption directly impacts battery life.

Deep learning models are energy-intensive due to:

- Large-scale computations
- Frequent data processing

Reinforcement learning further increases energy consumption due to continuous training cycles.

Federated learning reduces energy usage by minimizing data transmission but introduces communication overhead.

DKNN significantly improves energy efficiency by:

- Reducing model complexity
- Minimizing computation requirements

HCHO further enhances efficiency by:

- Eliminating unnecessary training iterations
- Optimizing convergence speed

As a result, DKNN-HCHO is highly suitable for **energy-constrained mobile environments**, making it a practical solution for 6G devices.

6. Security Robustness and Resistance to Advanced Attacks

Security robustness is a critical factor in evaluating AI-based defense systems.

Deep learning models are vulnerable to:

- Adversarial attacks
- Data poisoning
- Model inversion

Reinforcement learning models can be manipulated through:

- Malicious reward functions
- Environmental spoofing

Federated learning improves privacy but is susceptible to:

- Model poisoning attacks
- Gradient leakage

DKNN-HCHO enhances security robustness through:

- Compact and efficient feature representation (reduces attack surface)
- Optimized parameter tuning (improves stability)
- Improved generalization (resists adversarial perturbations)

Additionally, hybrid AI frameworks can integrate anomaly detection mechanisms to identify previously unseen attack patterns.

7. Practical Deployment Feasibility

Real-world deployment is often the biggest challenge for AI-based security systems.

Deep learning models require:

- High-performance hardware
- Large labeled datasets

Reinforcement learning models require:

- Extensive training time
- Continuous environment interaction

Federated learning faces challenges such as:

- Communication overhead
- Synchronization complexity

Quantum-based approaches remain largely theoretical due to hardware limitations.

DKNN-HCHO provides a more practical solution due to:

- Reduced computational requirements
- Faster training and inference
- Compatibility with edge devices

However, challenges remain in terms of:

- Standardization
- Integration with existing 6G infrastructure
- Hardware acceleration support

8. Holistic Comparative Insights

A holistic comparison reveals the following:

Approach	Strength	Weakness
Deep Learning	High accuracy	High computation
Reinforcement Learning	Adaptability	Slow convergence
Federated Learning	Privacy, scalability	Communication overhead
Hybrid DL	Robust performance	Complexity
DKNN	Efficient, lightweight	Emerging
DKNN-HCHO	Best balance	Needs real-world validation

9. Final Analytical Conclusion

The comprehensive analysis clearly establishes that:

DKNN-HCHO is the most promising AI framework for securing 6G mobile devices against side-channel attacks.

It uniquely combines:

- Efficiency (DKNN)
- Optimization (HCHO)
- Scalability (edge compatibility)
- Adaptability (dynamic tuning)
- Security robustness (resilient design)

This hybrid approach addresses the fundamental limitations of existing AI techniques and provides a next-generation solution for secure AI in 6G networks.

Trends in Secure AI for 6G

- AI-native security architecture
- Edge intelligence for real-time protection
- Quantum-enhanced security
- Adversarial AI defense mechanisms
- Energy-efficient AI models

Challenges

- High computational complexity
- Limited quantum hardware
- Data privacy concerns
- Real-time processing constraints
- Lack of standardization
- Energy consumption

Discussion

The integration of artificial intelligence into 6G mobile security represents a paradigm shift in how cyber threats are addressed. Traditional security mechanisms are no longer sufficient to counter advanced attacks such as side-channel attacks, which exploit physical vulnerabilities rather than software flaws. AI-driven approaches, particularly deep learning models, have demonstrated significant potential in detecting and mitigating these threats.

Deep learning models excel at analyzing complex patterns in side-channel data, enabling accurate detection of attack signatures. However, their high computational requirements limit their deployment in resource-constrained mobile devices. This challenge has led to the development of more efficient architectures such as Deep Kronecker Neural Networks.

DKNN reduces model complexity while maintaining high accuracy, making it suitable for mobile environments. When combined with Hybrid Cat Hunting Optimization, the model achieves faster convergence and improved

performance. This hybrid approach addresses key limitations of traditional deep learning models, including computational overhead and slow training.

Reinforcement learning and federated learning further enhance the adaptability and scalability of AI-based security systems. RL enables dynamic decision-making, while FL ensures data privacy in distributed environments. These approaches complement DKNN-HCHO, creating a comprehensive security framework.

Despite these advancements, challenges remain. AI models are vulnerable to adversarial attacks, and the lack of standardized frameworks hinders widespread adoption. Additionally, energy consumption and real-time processing requirements pose significant challenges.

Future research should focus on developing robust, scalable, and energy-efficient AI models for 6G security. The integration of quantum computing and edge intelligence holds significant potential for enhancing security and performance.

Conclusion

This paper presented a comprehensive review of artificial intelligence techniques for securing 6G mobile devices against side-channel attacks. The study highlighted the limitations of traditional security mechanisms and emphasized the importance of AI-driven approaches in addressing emerging threats.

The analysis demonstrated that deep learning, reinforcement learning, and federated learning play significant roles in enhancing security. Among these approaches, hybrid models such as DKNN-HCHO emerged as the most promising solution due to their ability to combine efficiency, accuracy, and scalability.

DKNN reduces computational complexity, while HCHO enhances optimization, resulting in improved performance and faster convergence. The integration of these techniques provides a robust framework for detecting and mitigating side-channel attacks in 6G mobile devices.

The study also identified key trends, including AI-native security architectures, edge intelligence, and quantum-enhanced security. These trends are expected to shape the future of 6G cybersecurity.

However, several challenges remain, including computational overhead, energy constraints, adversarial vulnerabilities, and lack of standardization. Addressing these challenges will be critical for the successful deployment of AI-based security systems.

Future research should focus on developing advanced hybrid models, improving hardware capabilities, and establishing standardized frameworks for AI integration in 6G networks. The combination of AI, quantum computing, and edge intelligence will play a crucial role in ensuring secure and efficient 6G communication systems.

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