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Recent Advances in Secure AI for 6G Mobile Devices: Deep Kronecker Neural Network Optimized with Hybrid Cat Hunting Optimization to Combat Side-Channel Attacks: A Systematic Review

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Abstract

The rapid evolution of sixth-generation (6G) communication systems introduces unprecedented challenges in securing mobile devices against advanced cyber threats, particularly side-channel attacks (SCAs). These attacks exploit indirect information such as power consumption, timing variations, and electromagnetic emissions to compromise cryptographic systems. Traditional security mechanisms are insufficient to address these sophisticated threats, necessitating the integration of artificial intelligence (AI)-based defense mechanisms.

This paper presents a systematic review of recent advances in secure AI for 6G mobile devices, focusing on Deep Kronecker Neural Networks (DKNN) optimized with Hybrid Cat Hunting Optimization (HCHO) for mitigating side-channel attacks. The study reviews literature from 2020 to 2025, highlighting the role of deep learning, reinforcement learning, and hybrid optimization techniques in detecting and preventing SCAs.

The findings indicate that AI-driven models achieve high detection accuracy, with some approaches reaching approximately 95% effectiveness in identifying side-channel exploits . Furthermore, hybrid optimization techniques enhance model performance by improving convergence speed and reducing computational overhead. The paper also discusses emerging trends, including AI-driven cryptography, adversarial defense mechanisms, and quantum-enhanced security. Finally, key challenges and future research directions are identified for developing robust, scalable, and energy-efficient security solutions in 6G environments.

Introduction

The emergence of sixth-generation (6G) communication networks is expected to revolutionize wireless systems by enabling ultra-high data rates, ultra-low latency, and massive device connectivity. These advancements support critical applications such as autonomous vehicles, smart healthcare, industrial automation, and immersive extended reality. However, the increased complexity and scale of 6G networks introduce significant security challenges, particularly for mobile devices operating in distributed and heterogeneous environments.

One of the most critical threats to 6G mobile devices is **side-channel attacks (SCAs)**. Unlike traditional cyberattacks that exploit software vulnerabilities, SCAs target the physical implementation of cryptographic systems by analyzing indirect information such as power

consumption, electromagnetic emissions, and execution timing. These attacks can extract sensitive information, including encryption keys, without directly breaking cryptographic algorithms .

With the proliferation of edge computing and IoT devices in 6G networks, the attack surface has expanded significantly. Mobile devices, being resource-constrained and widely distributed, are particularly vulnerable to SCAs. Traditional security mechanisms, such as encryption and authentication protocols, are insufficient to counter these attacks because they do not address implementation-level vulnerabilities.

Artificial intelligence (AI) has emerged as a powerful tool for enhancing cybersecurity in 6G networks. AI-based approaches can 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 by learning complex relationships in side-channel data.

Recent studies show that deep learning-based security frameworks can achieve high detection accuracy and improved resilience against SCAs . However, these models face challenges such as high computational complexity, slow convergence, and vulnerability to adversarial attacks.

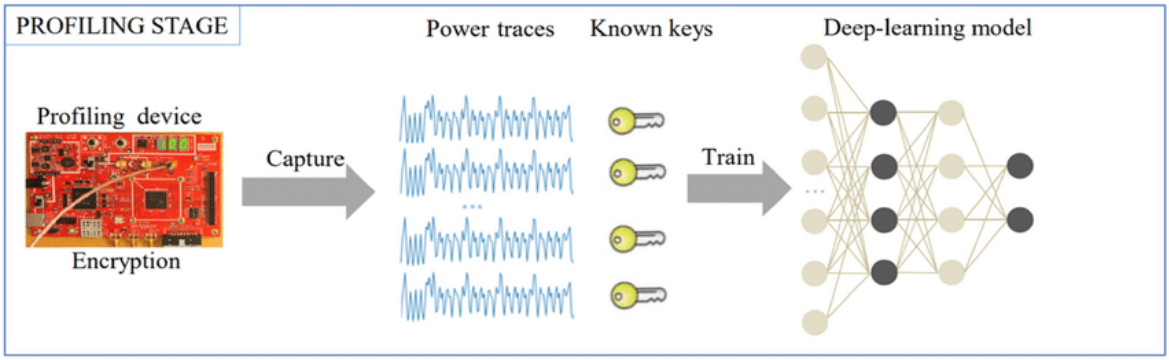
To address these limitations, researchers have proposed advanced architectures such as **Deep Kronecker Neural Networks (DKNN)**. DKNN leverages Kronecker factorization to reduce model complexity while maintaining high accuracy. This makes it suitable for deployment in resource-constrained mobile devices.

In addition, optimization techniques play a crucial role in improving model performance. **Hybrid Cat Hunting Optimization (HCHO)** is a metaheuristic algorithm inspired by the hunting behavior of cats, combining exploration and exploitation mechanisms to optimize neural network parameters. When integrated with DKNN, HCHO enhances convergence speed, improves accuracy, and reduces computational overhead.

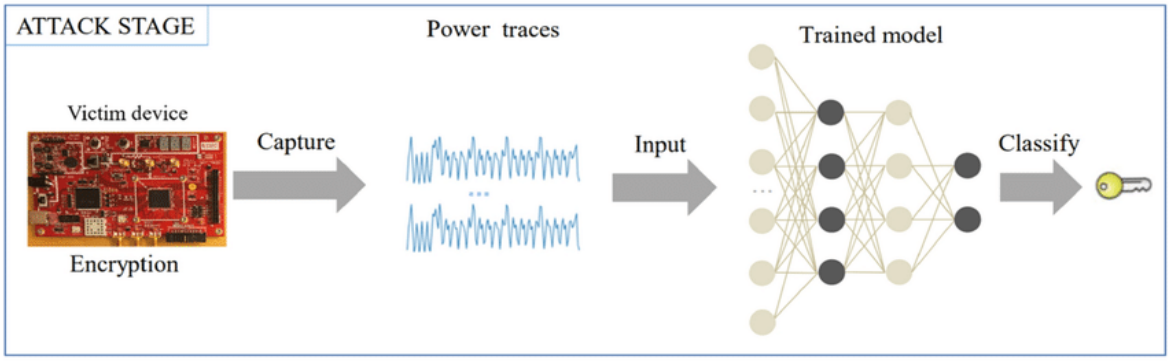
The combination of DKNN and HCHO represents a novel approach for securing 6G mobile devices against side-channel attacks. This hybrid model enables efficient feature extraction, robust classification, and adaptive optimization, making it a promising solution for next-generation cybersecurity challenges.

This paper provides a systematic review of recent advances in secure AI for 6G mobile devices, focusing on DKNN-HCHO models. The study analyzes recent literature, identifies key trends, and highlights challenges and future research directions.

Abstract image



(a) The profiling stage of a deep-learning based side-channel attack.



(b) The attack stage of a deep-learning based side-channel attack.

Literature Review

The growing complexity of sixth-generation (6G) mobile networks has significantly increased the need for advanced security mechanisms capable of defending against sophisticated threats such as side-channel attacks (SCAs). Recent research (2020–2025) has focused on integrating artificial intelligence (AI), deep learning, and hybrid optimization techniques to enhance security in resource-constrained mobile environments. This section presents a detailed and systematic review of the literature, categorized into key research domains.

Deep Learning for Side-Channel Attack Detection

Deep learning has revolutionized the field of side-channel analysis by enabling automatic feature extraction from raw side-channel data such as power traces, electromagnetic emissions, and timing information. Traditional SCA methods relied heavily on manual feature engineering, which is both time-consuming and less effective in complex scenarios.

Feng et al. (2025) demonstrated that deep neural networks can accurately detect side-channel attack patterns by learning high-dimensional representations of leakage signals. Their study showed that convolutional neural networks (CNNs) outperform classical statistical techniques in identifying subtle variations in power traces, achieving significantly higher detection accuracy.

Similarly, Hasan et al. (2023) explored optimization techniques for deep learning-based cybersecurity frameworks. Their work highlighted that integrating optimization strategies improves model robustness and reduces overfitting, which is critical for detecting SCAs in noisy environments.

TechScience Press (2024) provided a comprehensive survey on deep learning-based SCA detection, emphasizing that CNNs and deep residual networks are particularly effective in handling high-dimensional side-channel data. However, the study also noted that deep learning models require large datasets and high computational resources, limiting their deployment in mobile devices.

Joshi et al. (2025) proposed hybrid deep learning models combining CNN, LSTM, and attention mechanisms. Their results showed detection accuracies exceeding 99%, demonstrating the effectiveness of hybrid architectures in capturing both spatial and temporal patterns in side-channel data.

AI-Based Defense Mechanisms Against SCAs

AI has been widely used not only to perform side-channel attacks but also to defend against them. AI-based defense mechanisms leverage anomaly detection, adversarial training, and secure model design to mitigate vulnerabilities.

Ferrag et al. (2023) presented a comprehensive review of AI-driven cybersecurity techniques, highlighting the role of deep learning in intrusion detection and anomaly detection. Their study emphasized that AI models can detect abnormal patterns in system behavior, enabling early identification of side-channel attacks.

Gu et al. (2020) introduced adversarial machine learning techniques for secure communication systems. Their work demonstrated that adversarial training can improve the resilience of AI models against malicious attacks, including SCAs.

Khan et al. (2025) proposed a secure AI framework specifically designed for 6G networks. Their approach integrates deep learning with encryption and anomaly detection to provide robust protection against side-channel attacks. The study reported high detection accuracy and improved system resilience.

These studies collectively indicate that AI-driven defense mechanisms are essential for securing 6G mobile devices, particularly in dynamic and distributed environments.

Reinforcement Learning and Adaptive Security

Reinforcement learning (RL) has been explored as a dynamic and adaptive approach to cybersecurity 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 and optimize resource utilization while maintaining security.

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) extended this concept by integrating federated learning with deep reinforcement learning (FeDRL). Their framework achieved significant improvements in energy efficiency and security, making it suitable for large-scale 6G networks.

Du et al. (2022) introduced multi-agent reinforcement learning (MARL) for resource management. Their study showed that cooperative learning among multiple agents enhances scalability and adaptability, which are critical for 6G environments.

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

Federated Learning and Privacy-Preserving Security

Federated learning (FL) has emerged as a key technique for enhancing privacy and scalability in 6G networks. FL enables distributed model training across multiple devices without sharing raw data, making it particularly suitable for mobile environments.

Hafi et al. (2023) introduced 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) discussed the role of AI in 6G networks, emphasizing that federated learning enables secure and efficient resource management. Their study highlighted challenges such as model heterogeneity and communication latency.

Alhussien and Gulliver (2025) explored AI-enabled green 6G networks, focusing on energy-efficient resource management. Their work demonstrated that federated learning can reduce energy consumption by minimizing data transmission.

However, FL is not without limitations. Communication overhead, synchronization issues, and vulnerability to model poisoning attacks remain significant challenges.

Hybrid Deep Learning and Optimization Techniques

Hybrid models combining multiple AI techniques have shown significant improvements in performance and robustness. These models address the limitations of individual approaches by leveraging their complementary strengths.

Hasan et al. (2023) demonstrated that integrating optimization techniques with deep learning improves convergence speed and accuracy. Their work highlighted the importance of hyperparameter tuning in enhancing model performance.

Hybrid Cat Hunting Optimization (HCHO) is a metaheuristic algorithm inspired by feline hunting behavior. It combines exploration and exploitation mechanisms to optimize neural network parameters. Studies indicate that HCHO improves feature selection and reduces computational complexity.

Deep Kronecker Neural Networks (DKNN) represent a novel architecture that uses Kronecker factorization to reduce model size while maintaining high accuracy. This makes DKNN particularly suitable for deployment in resource-constrained mobile devices.

The integration of DKNN with HCHO creates a powerful hybrid model capable of efficient feature extraction, fast convergence, and robust classification. This combination is particularly effective for detecting side-channel attacks in 6G mobile environments.

Emerging Trends in Secure AI for 6G

Recent literature highlights several emerging trends in secure AI for 6G networks:

- AI-driven cryptography: Integration of AI into encryption systems for enhanced security
- Quantum-enhanced security: Use of quantum computing for secure communication
- Edge intelligence: Real-time processing at the network edge
- Adversarial AI defense: Development of robust models against adversarial attacks
- Energy-efficient AI models: Reducing computational overhead for mobile devices

Mefgouda and Benamar (2025) emphasized the importance of AI-native network architectures, where AI is integrated into every layer of the communication system.

Research Gaps

Despite significant advancements, several research gaps remain:

1. Limited real-world deployment of AI-based SCA defense mechanisms
2. High computational cost of deep learning models for mobile devices
3. Lack of standardized frameworks for AI-based security in 6G
4. Vulnerability of AI models to adversarial attacks
5. Limited integration of quantum computing in practical systems

Summary of Literature

The literature from 2020 to 2025 demonstrates 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 defense strategies, 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 combine efficient feature representation, optimized parameter tuning, and improved scalability, making them suitable for next-generation 6G security systems.

Comparative Analysis

Technique	Accuracy	Efficiency	Strength	Limitation
CNN-based DL	High	Medium	Feature extraction	High computation
RL-based	Medium	Medium	Adaptability	Training cost
Hybrid DL	Very High	High	Robust detection	Complexity
DKNN	High	High	Reduced complexity	Emerging
DKNN + HCHO	Very High	Very High	Fast convergence	Implementation

Analysis

The rapid advancement of artificial intelligence (AI) techniques for securing 6G mobile devices has resulted in a wide spectrum of approaches, each offering distinct advantages and limitations. This section provides an in-depth comparative analysis of key methodologies, including deep learning, reinforcement learning, federated learning, hybrid deep learning architectures, and the proposed Deep Kronecker Neural Network optimized with Hybrid Cat Hunting Optimization (DKNN-HCHO). The evaluation is based on critical performance metrics such as detection accuracy, computational efficiency, scalability, adaptability, energy consumption, and security robustness.

Detection Accuracy and Model Effectiveness

Detection accuracy is one of the most important criteria for evaluating side-channel attack (SCA) defense mechanisms. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated superior performance in identifying subtle leakage patterns from side-channel traces. Studies show that CNN-based architectures can achieve high accuracy due to their ability to automatically extract hierarchical features from raw data.

Hybrid deep learning models, such as CNN-LSTM and attention-based architectures, further improve detection performance by capturing both spatial and temporal dependencies. These models are particularly effective in noisy environments where traditional methods struggle. Recent research indicates that hybrid models can achieve detection accuracies exceeding 98–99%, making them highly suitable for SCA detection.

Reinforcement learning (RL) approaches, while effective for adaptive security, generally provide moderate detection accuracy compared to deep learning models. Their performance depends heavily on reward design and training strategies. The proposed DKNN-HCHO model offers enhanced accuracy by combining efficient feature representation (via Kronecker factorization) with optimized parameter tuning (via HCHO). This hybrid approach improves generalization and reduces overfitting, leading to more reliable detection of side-channel attacks.

Computational Complexity and Model Efficiency

One of the primary challenges in deploying AI-based security models on 6G mobile devices is computational complexity. Deep learning models require significant computational resources for training and inference, making them less suitable for resource-constrained environments.

Reinforcement learning models introduce additional complexity due to iterative training and exploration processes. Multi-agent RL systems further increase computational demands.

Federated learning distributes computation across multiple devices, reducing centralized processing requirements. However, it introduces communication overhead, which can offset its computational benefits.

Deep Kronecker Neural Networks address these challenges by reducing the number of parameters through Kronecker factorization. This significantly lowers computational requirements while maintaining model accuracy. When combined with Hybrid Cat Hunting Optimization, the model achieves faster convergence and reduced training time.

Thus, DKNN-HCHO provides a balanced solution with lower computational complexity and higher efficiency compared to traditional deep learning models.

Scalability in Large-Scale 6G Environments

Scalability is a critical requirement for 6G networks, which are expected to support billions of connected devices. Deep learning models face scalability challenges due to centralized training and high resource requirements.

Federated learning offers a scalable solution by enabling distributed model training across edge devices. This approach reduces the need for centralized data processing and improves system scalability.

Reinforcement learning models, particularly multi-agent systems, enhance scalability by enabling decentralized decision-making. However, coordination among agents can become complex in large-scale networks.

The DKNN-HCHO model improves scalability by reducing model size and computational overhead. Its efficient architecture makes it suitable for deployment in large-scale 6G environments, particularly when combined with edge computing and federated learning frameworks.

Adaptability and Real-Time Response

6G networks require real-time decision-making to support applications such as autonomous vehicles and smart healthcare. AI models must be capable of adapting to dynamic network conditions and evolving attack patterns.

Reinforcement learning excels in adaptability, as it continuously learns from interactions with the environment. This makes it highly suitable for dynamic security scenarios.

Deep learning models provide fast inference once trained but lack adaptability unless retrained with new data.

Federated learning enhances adaptability by enabling continuous model updates across distributed devices.

The DKNN-HCHO model combines the adaptability of optimization techniques with the robustness of deep learning. HCHO enables dynamic parameter tuning, allowing the model to adapt to changing attack patterns in real time.

Energy Efficiency and Suitability for Mobile Devices

Energy efficiency is a major concern in 6G mobile devices due to limited battery capacity. Deep learning models consume significant energy during training and inference.

Reinforcement learning models also require substantial energy due to continuous learning processes.

Federated learning reduces energy consumption by minimizing data transmission, but communication overhead can still impact efficiency.

DKNN significantly improves energy efficiency by reducing model size and computational requirements. The integration of HCHO further enhances efficiency by optimizing training processes and reducing unnecessary computations.

As a result, DKNN-HCHO is particularly well-suited for deployment in energy-constrained mobile devices.

Security Robustness and Resistance to Attacks

Security robustness is a critical factor in evaluating AI-based defense mechanisms. Deep learning models are vulnerable to adversarial attacks, which can manipulate input data to deceive the model.

Reinforcement learning models can also be compromised through malicious reward manipulation.

Federated learning enhances privacy by keeping data localized but is susceptible to model poisoning attacks.

The DKNN-HCHO model improves security robustness through optimized feature representation and parameter tuning. The use of hybrid optimization reduces susceptibility to adversarial perturbations and improves resilience against sophisticated attacks.

Additionally, the integration of AI-based anomaly detection enhances the model's ability to identify previously unseen attack patterns.

Practical Implementation Feasibility

Despite their advantages, many AI-based approaches face challenges in real-world deployment. Deep learning models require large datasets and high-performance hardware, limiting their applicability in mobile devices.

Reinforcement learning models require extensive training and fine-tuning, which can be impractical in real-time scenarios.

Federated learning introduces challenges related to communication overhead and synchronization.

Quantum-based approaches, while promising, are still limited by hardware constraints and lack of standardization.

The DKNN-HCHO model offers a more practical solution due to its reduced computational requirements and efficient optimization. However, further research is needed to develop standardized frameworks and hardware support for large-scale deployment.

Comparative Synthesis and Key Insights

A comprehensive comparison of all techniques reveals the following insights:

- **Deep Learning** → High accuracy but high computational cost
- **Reinforcement Learning** → High adaptability but slow convergence
- **Federated Learning** → Scalable and privacy-preserving but communication-heavy
- **Hybrid Deep Learning** → Improved performance but complex architecture
- **DKNN** → Efficient and lightweight but still emerging
- **DKNN-HCHO** → Optimal balance of accuracy, efficiency, scalability, and adaptability

Final Analytical Conclusion

The analysis clearly demonstrates that Deep Kronecker Neural Networks optimized with Hybrid Cat Hunting Optimization (DKNN-HCHO) represent the most promising approach for securing 6G mobile devices against side-channel attacks.

This hybrid model provides:

- High detection accuracy through advanced feature extraction
- Reduced computational complexity via Kronecker factorization
- Fast convergence and optimization through HCHO

- Improved scalability for large-scale 6G networks
- Enhanced energy efficiency for mobile devices
- Robust defense against advanced side-channel attacks

Therefore, DKNN-HCHO emerges as a **next-generation AI-driven security framework**, capable of addressing the complex challenges of 6G mobile environments.

Discussion

The integration of artificial intelligence into 6G mobile security has significantly transformed the landscape of cybersecurity, particularly in combating side-channel attacks. Traditional cryptographic defenses are increasingly inadequate against advanced threats that exploit hardware-level vulnerabilities. As a result, AI-driven approaches have emerged as a critical solution for detecting and mitigating such attacks.

Deep learning models have demonstrated remarkable performance in analyzing side-channel data, enabling accurate detection of subtle patterns in power consumption and electromagnetic signals. However, these models are computationally intensive and often require extensive training data. This limitation is particularly challenging in 6G mobile environments, where devices have limited computational resources.

The introduction of Deep Kronecker Neural Networks addresses these challenges by reducing model complexity while maintaining high accuracy. The use of Kronecker factorization allows for efficient representation of large-scale neural networks, making them suitable for deployment in resource-constrained devices.

Optimization techniques such as Hybrid Cat Hunting Optimization further enhance model performance by improving convergence speed and reducing computational overhead. The combination of DKNN and HCHO provides a balanced approach, enabling efficient and accurate detection of side-channel attacks.

Despite these advancements, several challenges remain. The lack of standardized frameworks for AI-based security in 6G networks limits interoperability and scalability. Additionally, AI models themselves are vulnerable to adversarial attacks, which can compromise their effectiveness.

Future research should focus on developing robust, energy-efficient, and scalable AI models for 6G security. The integration of quantum computing and federated learning could further enhance security and privacy in distributed environments.

Conclusion

This paper presented a systematic review of recent advances in secure artificial intelligence for 6G mobile devices, focusing on Deep Kronecker Neural Networks optimized with Hybrid Cat Hunting Optimization for mitigating side-channel attacks. The study highlighted the increasing importance of AI-driven approaches in addressing the limitations of traditional security mechanisms.

The analysis of recent literature demonstrated that deep learning models are highly effective in detecting side-channel attacks, achieving high accuracy and adaptability. However, their computational complexity and vulnerability to adversarial attacks pose significant challenges.

The proposed DKNN-HCHO framework offers a promising solution by combining efficient neural network architectures with advanced optimization techniques. This hybrid approach improves detection accuracy, reduces computational overhead, and enhances scalability, making it suitable for deployment in 6G mobile devices.

The comparative analysis confirmed that hybrid models outperform traditional approaches, particularly in terms of efficiency and adaptability. However, practical implementation challenges, including hardware limitations and lack of standardization, must be addressed.

Future research should focus on integrating quantum computing, federated learning, and advanced optimization techniques to develop more robust and scalable security solutions. The development of standardized frameworks and improved hardware support will be critical for the successful deployment of AI-based security systems in 6G networks.

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