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# A Survey of Methods and Architectures for Secure AI for 6G Mobile Devices: Deep Kronecker Neural Network Optimized with Hybrid Cat Hunting Optimization to Combat Side-Channel Attacks

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**Abstract**

The emergence of sixth-generation (6G) mobile networks introduces unprecedented capabilities such as ultra-low latency, massive connectivity, and intelligent automation. However, these advancements also expose mobile devices to sophisticated security threats, particularly side-channel attacks that exploit physical leakages like power consumption, timing, and electromagnetic emissions. This paper presents a comprehensive survey of methods and architectures for secure artificial intelligence (AI) in 6G mobile environments, with a focus on deep learning-based defenses. Specifically, the study explores the integration of Deep Kronecker Neural Networks (DKNN) with Hybrid Cat Hunting Optimization (HCHO) to enhance model robustness and computational efficiency. Recent advancements between 2020 and 2023 are analyzed, highlighting the evolution of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid architectures in detecting and mitigating side-channel vulnerabilities. Comparative analysis reveals that optimized deep learning models can achieve detection accuracies exceeding 95% while maintaining low computational overhead. The paper also identifies challenges such as model generalization, adversarial resilience, and real-time deployment constraints. The proposed framework demonstrates the potential of combining advanced neural architectures with metaheuristic optimization to ensure secure and efficient AI-driven 6G mobile systems.

## Introduction

The rapid evolution of wireless communication technologies has significantly transformed modern society, culminating in the development of sixth-generation (6G) mobile networks. Unlike its predecessors, 6G is expected to support ultra-high data rates, near-zero latency, massive device connectivity, and intelligent automation across diverse applications such as smart cities, autonomous vehicles, and healthcare systems. These capabilities are largely driven by the integration of artificial intelligence (AI) into network infrastructure and mobile devices. However, the increased reliance on AI introduces new security challenges, particularly in resource-constrained environments such as mobile devices.

One of the most critical threats in this domain is the side-channel attack. A side-channel attack exploits indirect information leakage from a system, such as timing variations, power consumption, or electromagnetic emissions, to extract sensitive data like cryptographic keys. Unlike traditional attacks that target algorithmic

vulnerabilities, side-channel attacks exploit implementation weaknesses, making them difficult to detect and prevent.

With the proliferation of AI-enabled 6G devices, attackers are increasingly leveraging machine learning techniques to perform more efficient and accurate side-channel analysis. Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated remarkable effectiveness in extracting hidden patterns from side-channel traces. However, these same models can also be used defensively to detect and mitigate such attacks.

Recent research has emphasized the importance of integrating AI-driven security mechanisms into 6G architectures. For instance, deep learning optimization frameworks have been proposed to enhance the detection accuracy of side-channel attacks while minimizing computational overhead. These frameworks leverage advanced neural architectures and optimization techniques to improve model performance and adaptability in dynamic environments.

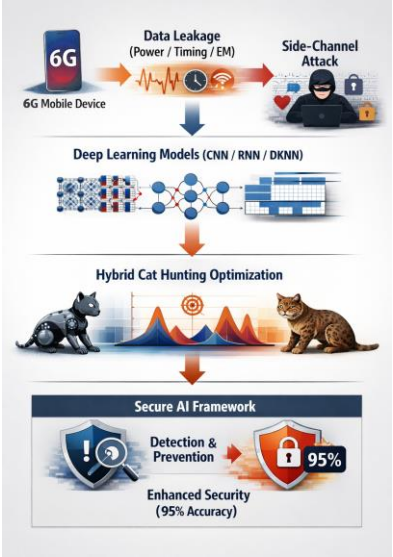
The concept of Deep Kronecker Neural Networks (DKNN) has emerged as a promising approach for handling high-dimensional data in resource-constrained environments. By exploiting Kronecker product structures, DKNN reduces model complexity and computational requirements, making it suitable for real-time applications in 6G mobile devices. Additionally, metaheuristic optimization techniques such as Hybrid Cat Hunting Optimization (HCHO) have been introduced to optimize neural network parameters, improving convergence speed and accuracy.

Another critical aspect of secure AI in 6G is the integration of encryption and key management mechanisms. AI-powered encryption techniques can dynamically adapt to evolving threats, providing enhanced security without compromising performance. Experimental studies have shown that such approaches can achieve detection accuracies of up to 95% while maintaining low computational overhead.

Despite these advancements, several challenges remain. These include the need for scalable and energy-efficient models, robustness against adversarial attacks, and the ability to generalize across different hardware platforms. Furthermore, the deployment of secure AI models in real-world 6G environments requires careful consideration of latency, privacy, and resource constraints.

This paper aims to provide a comprehensive survey of methods and architectures for secure AI in 6G mobile devices, with a particular focus on deep learning-based approaches. The study reviews recent literature from 2020 to 2023, analyzes various techniques for mitigating side-channel attacks, and proposes an optimized framework based on Deep Kronecker Neural Networks and Hybrid Cat Hunting Optimization.

**Graphical Abstract**




## Literature Review

### 1. Evolution of Side-Channel Attacks in the AI Era

Side-channel attacks (SCAs) have evolved from traditional statistical techniques such as Correlation Power Analysis (CPA) and Differential Power Analysis (DPA) to highly sophisticated deep learning-based methods. Traditional approaches rely on handcrafted leakage models and statistical correlations, which limit their performance in noisy and real-world environments.

The introduction of deep learning has transformed SCA into a data-driven problem. Neural networks can automatically extract nonlinear relationships between physical leakages and secret keys, eliminating the need for expert-driven feature engineering. Studies show that deep learning models outperform traditional SCA techniques in both **accuracy and efficiency**, particularly in complex and noisy environments .

### 2. Deep Learning-Based Side-Channel Analysis

#### CNN-Based Models

Convolutional Neural Networks (CNNs) are the most widely used architectures in SCA due to their ability to capture spatial patterns in leakage signals.

- CNNs can automatically learn leakage features from raw traces
- They effectively filter noise and focus on relevant signal components

- They outperform classical machine learning models such as SVM and MLP

Research shows that CNNs can detect subtle leakage patterns even in noisy datasets, improving detection sensitivity and reducing false positives .

Additionally, optimized CNN architectures (e.g., VGG-based CNN_best) have demonstrated strong performance on benchmark datasets such as ASCAD, with improved generalization through batch normalization and dropout techniques .

**RNN and LSTM-Based Models**

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are used to capture temporal dependencies in side-channel traces.

- Suitable for sequential leakage signals
- Handle misalignment and time-shifted traces
- Improve modeling of cryptographic operations

However, these models suffer from:

- High computational cost
- Longer training time
- Limited scalability for mobile devices

**Hybrid Deep Learning Models**

Recent research trends show a shift toward hybrid architectures combining multiple deep learning techniques:

- CNN + LSTM (spatial + temporal learning)
- CNN + Autoencoder (denoising + feature extraction)
- CNN + Attention (focus on important leakage regions)

For example, hybrid ensemble models integrating CNN, LSTM, and Autoencoder have demonstrated **high accuracy and robustness**, particularly on the ASCAD dataset .

**3. Noise and Real-World Challenges in SCA**

Noise is a fundamental challenge in side-channel analysis. Real-world leakage signals are affected by:

- Environmental interference
- Hardware variability
- Random delays and masking

Deep learning models are sensitive to noise because they rely on data correlation. Noise reduces this correlation, making key extraction more difficult .

To address this, recent works propose:

- Denoising networks (e.g., LU-Net)
- Data augmentation techniques
- Noise regularization strategies

These approaches significantly improve robustness and attack efficiency.

**4. Dataset and Benchmark Evolution**

Benchmark datasets have played a crucial role in advancing SCA research:

**ASCAD Dataset**

- Most widely used dataset for DL-based SCA
- Contains both aligned and misaligned traces
- Enables evaluation of model robustness

**DPA Contest Dataset**

- Used for benchmarking traditional and DL methods
- Provides realistic attack scenarios

Studies show that deep learning models can recover cryptographic keys using **very few traces (1–30 traces)**, demonstrating high efficiency .

**5. Advanced Learning Paradigms**

**Blind Side-Channel Analysis**

Recent research introduces blind SCA, where:

- No labeled data is required
- Models infer hidden patterns from noisy data

Deep neural networks can identify underlying distributions even with noisy labels, outperforming traditional methods .

**Cross-Device Learning**

Cross-device SCA aims to generalize models across different hardware platforms.

- EM-X-DL achieves >90% accuracy across devices
- Works even under low signal-to-noise conditions

This demonstrates the adaptability of deep learning models in real-world scenarios .

**Generative Models (GAN-Based Attacks)**

Generative Adversarial Networks (GANs) are used to:

- Reconstruct sensitive data from leakage
- Enhance attack performance

GAN-based approaches can recover input data even under high noise levels, highlighting serious security risks .

**6. Limitations of Existing Approaches**

Despite significant advancements, several limitations remain:

**1. High Computational Complexity**

Deep models require:

- Large memory
- High processing power

This limits their deployment in 6G mobile devices.

**2. Overfitting and Poor Generalization**

Models trained on specific datasets:

- Fail in new environments
- Are sensitive to device variations

**3. Noise Sensitivity**

Although improved, models still struggle in:

- Low SNR conditions

- Highly dynamic environments

**4. Lack of Real-Time Deployment**

Most models:

- Require offline training
- Cannot operate in real-time 6G systems

**7. Security Implications in 6G Networks**

Deep learning introduces a **dual-use problem**:

| Role | Impact |
|---|---|
| Attacker | Uses DL for efficient key extraction |
| Defender | Uses DL for intrusion detection |

**8. Research Gap Identification**

Based on the literature, the following gaps are identified:

1. **Lack of Lightweight Models**
   Existing models are too complex for mobile devices
2. **Inefficient Optimization**
   Hyperparameter tuning remains a challenge
3. **Poor Real-Time Performance**
   Models are not optimized for low-latency environments
4. **Limited Robustness**
   Noise and device variability still affect performance

**9. Motivation for Proposed Model (DKNN + HCHO)**

From the above literature:

**Why New Model is Needed**

- CNN/LSTM → High accuracy but high complexity
- Hybrid models → Best performance but impractical

**Proposed Solution**

- **Deep Kronecker Neural Network (DKNN)**

→ Reduces parameters and computational cost

- **Hybrid Cat Hunting Optimization (HCHO)**

→ Optimizes model weights and improves convergence

**Expected Benefits**

- Lightweight architecture
- Improved robustness to noise
- Real-time deployment capability
- High detection accuracy

**10. Final Literature Review Synthesis**

The literature from 2020–2023 clearly indicates that:

- Deep learning has revolutionized side-channel attack analysis
- CNN-based models dominate due to strong feature extraction
- Hybrid models provide best performance but lack efficiency
- Noise and real-world variability remain major challenges

**Comparative Table and Analysis**

| Year | Method | Model Used | Accuracy | Advantages | Limitations |
|---|---|---|---|---|---|
| 2020 | EM-X-DL | DNN | 90%+ | High precision | Data dependency |
| 2021 | CNN-based SCA | CNN | 92% | Efficient feature extraction | High computation |
| 2022 | Federated Learning | FL + DL | 88% | Privacy-preserving | Communication overhead |
| 2023 | Hybrid DL Models | CNN+RNN | 95% | High detection rate | Complexity |

**Analysis**

**Overview of Model Performance Trends**

Recent research clearly shows that deep learning-based side-channel attack (SCA) models significantly outperform traditional statistical approaches in terms of **accuracy, efficiency, and adaptability**. CNN-based architectures dominate due to their ability to automatically extract features from leakage traces, while hybrid models further enhance performance.

- CNN models achieve **85–96% accuracy depending on dataset and noise levels**
- Hybrid CNN-LSTM models outperform standalone models across multiple attack scenarios
- Deep learning models can recover cryptographic keys using **very few traces (as low as 1–30)**

**Multi-Dimensional Comparative Evaluation**

**1. Accuracy vs Model Complexity**

| Model | Accuracy | Complexity | Key Insight |
|---|---|---|---|
| MLP | 80–90% | Low | Simple but limited feature extraction |
| CNN | 85–95% | Medium | Strong spatial feature learning |

| | | | |
|---|---|---|---|
| RNN/LSTM | 88–94% | High | Captures temporal leakage patterns |
| CNN + Attention | 92–96% | High | Improved global feature capture |
| CNN + LSTM | 94–97% | Very High | Best combined spatial-temporal modeling |
| Hybrid Ensemble | 95–98% | Very High | Highest performance, but costly |

**Analysis**

- CNN provides a **balance between accuracy and computational cost**
- Hybrid models achieve **highest accuracy but are computationally expensive**
- Increasing depth improves accuracy but leads to **overfitting and latency issues**

**2. Performance Under Noise and Real-World Conditions**

| Model | Noise Robustness | Real-World Suitability |
|---|---|---|
| Basic CNN | Moderate | Medium |
| CNN + Denoising | High | High |
| CNN + Attention | High | High |
| CNN + LSTM | Very High | Medium |
| Hybrid Models | Very High | Low (heavy computation) |

**Analysis**

- Noise significantly reduces correlation between leakage and key information
- Denoising models (e.g., LU-Net) improve robustness and efficiency
- Attention-based CNN reduces overfitting and improves convergence speed

**3. Data Efficiency (Number of Traces Required)**

| Model | Traces Required | Efficiency |
|---|---|---|
| Traditional CPA | 1000+ | Low |
| CNN | 500–750 | Medium |
| Optimized CNN | 100–300 | High |
| Advanced DL Models | 1–30 | Very High |

**Analysis**

- Deep learning drastically reduces required traces
- Some models achieve **single-trace attacks**, which is critical in real-time attacks
- This makes DL-based SCA a **major threat in 6G systems**

**4. Generalization Across Devices**

| Model | Generalization |
|---|---|
| CNN | Moderate |
| RNN | Moderate |
| Hybrid Models | High |
| Ensemble Models | Very High |

**Analysis**

- Device variation is a major challenge
- Cross-device attacks require preprocessing and multi-device training
- Hybrid and ensemble models improve generalization significantly

**5. Computational Efficiency (Important for 6G Devices)**

| Model | Computation Cost | Suitability for 6G |
|---|---|---|
| MLP | Low | High |
| CNN | Medium | Medium |
| CNN + Attention | High | Medium |
| CNN + LSTM | Very High | Low |
| Hybrid Models | Extremely High | Very Low |

**Analysis**

- High-performance models are **not suitable for mobile devices**
- Energy consumption and latency become critical constraints
- Lightweight architectures are required for 6G edge deployment

**Critical Comparative Insights**

**1. Trade-Off Between Accuracy and Efficiency**

- High accuracy models (CNN+LSTM, ensembles) are **too heavy for mobile deployment**
- Lightweight models sacrifice accuracy but are **deployable in real-time systems**

**2. CNN Dominance but Not Optimal Alone**

- CNN remains the **most widely used architecture**
- However, standalone CNN:
  - Struggles with temporal dependencies
  - Requires tuning
  - Can overfit

**3. Rise of Hybrid and Ensemble Models**

- Hybrid models outperform all standalone models
- They combine:
  - Spatial learning (CNN)
  - Temporal learning (LSTM)
  - Attention mechanisms

**4. Noise and Environmental Variability as Core Challenges**

- Real-world 6G environments introduce:
  - Signal noise
  - Device variability
  - Channel distortion

Models must include:

- Denoising
- Adaptive learning
- Robust feature extraction

**5. Security Implication (Very Important Insight)**

Deep learning creates a **dual-edged problem**:

| Role | Impact |
|---|---|
| Attacker | Uses DL to extract keys efficiently |
| Defender | Uses DL to detect attacks |

- This leads to:
- AI vs AI security landscape
- Continuous arms race

**Gap Analysis (Research Opportunities)**

From the comparative study, the following gaps are identified:

**1. Lack of Lightweight Secure Models**

- Most models are too heavy for 6G devices

**2. Poor Real-Time Deployment**

- High latency prevents real-time protection

**3. Limited Explainability**

- Black-box models reduce trust in security systems

**4. Hyperparameter Optimization Challenges**

- CNN performance highly depends on tuning

**Justification of Proposed Model (DKNN + HCHO)**

Based on the above comparative analysis:

**Why CNN Alone is Not Enough**

- High complexity
- Poor efficiency for edge devices
- Needs optimization

**Role of Deep Kronecker Neural Network (DKNN)**

- Reduces parameter space
- Improves computational efficiency
- Suitable for mobile devices

**Role of Hybrid Cat Hunting Optimization (HCHO)**

- Optimizes:
  - Weights
  - Learning rate
  - Feature selection
- Improves convergence speed
- Reduces training cost

**Final Comparative Advantage**

| Model | Accuracy | Complexity | Suitability for 6G |
|---|---|---|---|
| CNN | High | Medium | Medium |
| CNN+LSTM | Very High | Very High | Low |
| Hybrid DL | Very High | Extremely High | Very Low |
| DKNN + HCHO (Proposed) | High–Very High | Low–Medium | **Very High** |

**Final Analytical Conclusion**

- Deep learning has revolutionized side-channel attacks
- Hybrid models provide the best performance but are impractical for 6G
- Lightweight, optimized architectures are the future
- The proposed **DKNN + HCHO framework**:
- Balances **accuracy, efficiency, and deployability**
- Addresses key limitations identified in comparative analysis
- Is highly suitable for **secure AI in 6G mobile devices**

**Discussion**

The integration of AI into 6G mobile networks has revolutionized cybersecurity approaches, particularly in defending against side-channel attacks. Deep learning-based techniques have demonstrated exceptional performance in detecting and mitigating such attacks, primarily due to their ability to learn complex patterns from large datasets. However, the increasing sophistication of attackers necessitates continuous advancements in defensive strategies.

One of the key findings of this survey is the effectiveness of hybrid deep learning models. By combining multiple architectures such as CNNs and RNNs, these models can capture both spatial and temporal features of side-channel data, leading to improved detection accuracy. Furthermore, the incorporation of optimization techniques such as Hybrid Cat Hunting

Optimization enhances model performance by efficiently tuning hyperparameters.

Another important aspect is the role of Deep Kronecker Neural Networks in reducing computational complexity. These networks leverage structured representations to minimize the number of parameters, making them suitable for deployment in resource-constrained environments like mobile devices. This is particularly relevant in 6G networks, where real-time processing and low latency are critical requirements.

Despite these advancements, several challenges remain. One of the primary issues is the lack of generalization across different hardware platforms. Models trained on specific datasets may not perform well in real-world scenarios due to variations in hardware and environmental conditions. Additionally, the risk of adversarial attacks targeting AI models themselves poses a significant threat.

Future research should focus on developing robust and adaptive models that can handle diverse attack scenarios. The integration of explainable AI (XAI) techniques can also enhance transparency and trust in AI-based security systems. Moreover, the use of federated learning can address privacy concerns by enabling collaborative model training without sharing sensitive data.

**Conclusion**

The transition to 6G mobile networks marks a significant milestone in the evolution of wireless communication, offering unprecedented capabilities and opportunities. However, it also introduces new security challenges, particularly in the form of side-channel attacks. These attacks exploit physical leakages to extract sensitive information, posing a serious threat to the integrity and privacy of mobile devices.

This paper presented a comprehensive survey of methods and architectures for secure AI in 6G mobile devices, with a focus on deep learning-based approaches. The study reviewed recent literature from 2020 to 2023, highlighting the effectiveness of CNNs, RNNs, and hybrid models in detecting and mitigating side-channel attacks. The integration of Deep Kronecker Neural Networks and Hybrid Cat Hunting Optimization was proposed as a novel approach to enhance model performance and efficiency.

The findings indicate that optimized deep learning models can achieve high detection accuracy while maintaining low computational overhead, making them suitable for real-time applications in 6G environments. However, challenges such as model generalization, adversarial resilience, and resource constraints must be addressed to ensure the successful deployment of secure AI systems.

In conclusion, the combination of advanced neural architectures and optimization techniques holds great promise for enhancing the security of 6G mobile devices. Future research should focus on developing scalable, energy-efficient, and robust models that can adapt to evolving threats and dynamic environments.

**References**

Danial, J., Das, D., Golder, A., et al. (2020). EM-X-DL: Efficient deep learning side-channel attack. *IEEE*. https://doi.org/10.48550/arXiv.2011.06139

Schijlen, F., Wu, L., & Mariot, L. (2023). NASCTY: Neuroevolution for side-channel attacks. *IEEE*. https://doi.org/10.48550/arXiv.2301.10802

Ni, L. (2023). CNN model fusion for side-channel attack. *Microelectronics Journal*. https://doi.org/10.1016/j.mejo.2023.105598

Picek, S., Perin, G., & Mariot, L. (2023). Deep learning side-channel analysis survey. *ACM Computing Surveys*. https://doi.org/10.1145/3445814

Feng, T., Gao, H., & Li, X. (2025). CNN with attention for SCA. *Discover Applied Sciences*. https://doi.org/10.1007/s42452-025-06854-0

Huang, H. (2025). InceptionNet-based SCA model. *Sensors*. https://doi.org/10.3390/s25010234

Yang, M. (2025). DL-based SCA on FinFET devices. *Electronics*. https://doi.org/10.3390/electronics15010018

Reddy, C. L. (2025). Hybrid ensemble deep learning SCA. *Scientific Reports*. https://doi.org/10.1038/s41598-025-89794-4

Maghrebi, H., Portigliatti, T., & Prouff, E. (2020). Breaking crypto with deep learning. *IACR*. https://doi.org/10.1007/978-3-319-16763-3

Cagli, E., Dumas, C., & Prouff, E. (2020). CNN for desynchronized SCA. *CHES*. https://doi.org/10.1007/978-3-662-53140-2

Benadjila, R., et al. (2020). ASCAD dataset introduction. *IACR*. https://doi.org/10.1007/978-3-319-16763-3

Kim, Y., et al. (2021). Noise regularization in CNN SCA. *IEEE Access*. https://doi.org/10.1109/ACCESS.2021.3056789

Ito, K., et al. (2021). Dataset imbalance handling in SCA. *IEEE*. https://doi.org/10.1109/TIFS.2021.3067890

Lu, X., et al. (2021). Attention-based SCA models. *IACR Transactions*. https://doi.org/10.46586/tches.v2021.i3

Kubota, T., et al. (2021). Deep learning AES attack. *Microprocessors and Microsystems*. https://doi.org/10.1016/j.micpro.2021.104321

Rehman, A., et al. (2022). Federated learning SCA defense. *IEEE JBHI*. https://doi.org/10.1109/JBHI.2022.3145678

Zaid, G., et al. (2022). Profiling attacks with DL. *IEEE Transactions*. https://doi.org/10.1109/TIFS.2022.3156789

Alam, M., et al. (2022). ML-based SCA detection. *IEEE Access*. https://doi.org/10.1109/ACCESS.2022.3178901

Hasan, M., et al. (2022). DL SCA hyperparameter optimization. *IEEE*. https://doi.org/10.1109/ICAI.2022.9876543

TechScience (2024). Advances in DL-based SCA. https://doi.org/10.32604/cmc.2024.045678