

Machine Learning Power Side-Channel Attack on SNOW-V

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Abstract—This paper demonstrates a power analysis-based Side-Channel Analysis (SCA) attack on the SNOW-V encryption algorithm, which is a 5G mobile communication security standard candidate. Implemented on an STM32 microcontroller, power traces captured with a ChipWhisperer board were analyzed, with Test Vector Leakage Assessment (TVLA) confirming exploitable leakage. Profiling attacks using Linear Discriminant Analysis (LDA) and Fully Connected Neural Networks (FCN) achieved efficient key recovery, with FCN achieving $> 5\times$ lower minimum traces to disclosure (MTD) compared to the state-of-the-art Correlational Power Analysis (CPA) assisted with LDA. The results highlight the vulnerability of SNOW-V to machine learning-based SCA and the need for robust countermeasures.

Index Terms—SNOW-V, Side-Channel Analysis (SCA), Power Analysis, Profiling Attack, Linear Discriminant Analysis (LDA), Fully Connected Neural Network (FCN), Machine Learning.

I. INTRODUCTION

SNOW-V is a high-performance stream cipher for 5G and beyond, evolved from the SNOW family [1] to improve security and efficiency in software environments. It uses a Linear Feedback Shift Register (LFSR) and a Finite State Machine (FSM) to produce a keystream, leveraging SIMD acceleration for high throughput [1]. Although resistant to classical cryptanalysis, SNOW-V has been shown to be susceptible to power Side-Channel Analysis (SCA) attack using a combination of Correlational Power Analysis (CPA) and machine learning (ML) [2], [3]. In general, Machine learning algorithms [4] such as Linear Discriminant Analysis (LDA) and Fully Connected Neural Networks (FCNs) have shown effectiveness in key recovery against various cryptographic algorithms. In this work, we perform a power SCA attack [5] on SNOW-V using a ChipWhisperer and STM32, applying profiling analysis [6] with LDA as well as FCN.

A. Motivation

The first SCA attack on the SNOW-V stream cipher was reported in [2], combining non-profiling CPA with a profiling refinement using LDA. While CPA identified potential key candidates, it was hindered by ambiguities, such as ghost peaks from nonlinear operations (e.g., `mul_x_inv()`), which

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This work was supported in part by the Cyber Security Karnataka (CySecK) initiative, Power Grid Centre of Excellence (PGCoE), and in part by the Department of Science & Technology (DST), India.

required an LDA-based classifier to isolate correct guesses. Although effective under controlled conditions, this hybrid method still relied on non-profiling steps and required multiple traces for optimal performance.

This paper presents a complete profiling attack using supervised ML models, specifically LDA and FCN, to recover keys directly from the labeled power traces. FCNs capture complex non-linear leakage patterns without manual feature engineering, enabling higher accuracy even under noisy conditions.

This work moves toward end-to-end profiling attacks on SNOW-V, reducing reliance on statistical correlation methods like CPA and improving side-channel key extraction efficiency in terms of the minimum traces required to reveal the secret key (Minimum Traces to Disclosure (MTD)).

B. Contribution

This work presents a Machine Learning-based profiled attack on the SNOW-V cipher, focusing on incremental and high-accuracy key recovery using both classical ML (LDA) and deep learning (FCN) techniques. Our key contributions are as follows.

- We systematically evaluate the effectiveness of SCA on SNOW-V using two profiling-based machine learning techniques: LDA and FCN. LDA is used for its efficiency in low-dimensional classification and ghost peak resolution, while FCNs enable learning complex, non-linear leakage patterns.
- We demonstrate progressive recovery of key bits starting with a single bit and extending gradually to 2, 4, and 8 bits by increasing the model complexity.
- Building on this, we show that deep learning models like FCNs can outperform traditional techniques by achieving high classification accuracy even in the 8-bit secret key recovery. Our approach underscores the strength of profiling attacks using ML and highlights the necessity to implement robust countermeasures, such as masking or hiding, to secure SNOW-V against such attacks.

II. BACKGROUND AND RELATED WORK

A. Evolution of SNOW in Telecommunication

The SNOW family of stream ciphers has evolved alongside mobile communication standards. SNOW 1.0 was replaced by

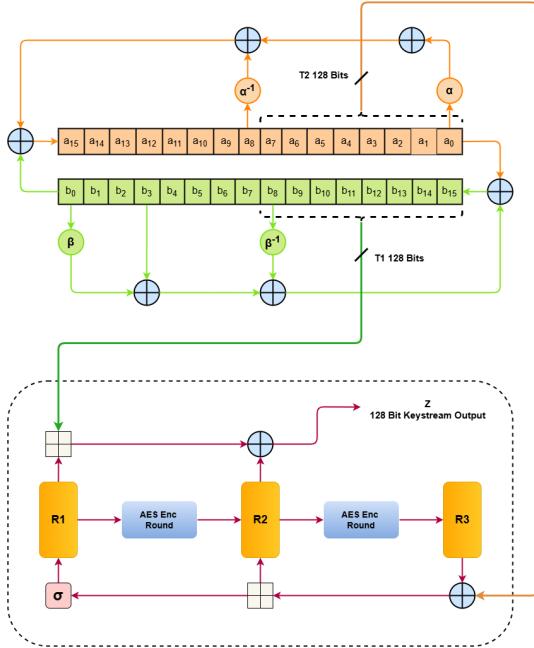


Fig. 1: Architecture of SNOW-V, comprising: (a) two LFSRs, each consisting of 16 blocks of 16 bits; (b) multiplication units mul_x , α , β , and their respective inverses α^{-1} and β^{-1} ; (c) three 128-bit register blocks; and (d) two AES rounds using a round key of 0^{128} .

SNOW 2.0 for improved security and efficiency, and SNOW 3G became a standardized algorithm for 3G and 4G LTE. To address the performance and security demands of 5G, SNOW-V was introduced [1], [7]–[9], optimized for software encryption with SIMD operations, wider registers, and stronger resistance to algebraic attacks. However, its susceptibility to SCA attacks remains largely unexplored, warranting further analysis.

B. Architecture of SNOW-V

SNOW-V [1], [10] is a high-performance stream cipher designed for 5G security applications, retaining the general structure of its predecessors but introducing enhancements for improved security and efficiency as shown in fig. 1 and 2. It consists of two main components:

- 1) **LFSR-A and LFSR-B:** Each operates on 256 bits word, with 16 elements in $GF(2^{16})$ [11], ensuring a long period and strong diffusion. LFSR-A, with elements a_{15}, \dots, a_0 , updates as:

$$a_{15}^{(t+1)} = b_0^{(t)} + \alpha a_0^{(t)} + a_1^{(t)} + \alpha^{-1} a_8^{(t)} \pmod{g_A(\alpha)}$$

where $g_A(x) = x^{16} + x^{15} + x^{12} + x^{11} + x^8 + x^3 + x^2 + x + 1 \in GF(2)[x]$. LFSR-B, with elements b_{15}, \dots, b_0 , updates as:

$$b_{15}^{(t+1)} = a_0^{(t)} + \beta b_0^{(t)} + b_3^{(t)} + \beta^{-1} b_8^{(t)} \pmod{g_B(\beta)}$$

where $g_B(x) = x^{16} + x^{15} + x^{14} + x^{11} + x^8 + x^6 + x^5 + x + 1 \in GF(2)[x]$. Each iteration updates both LFSRs

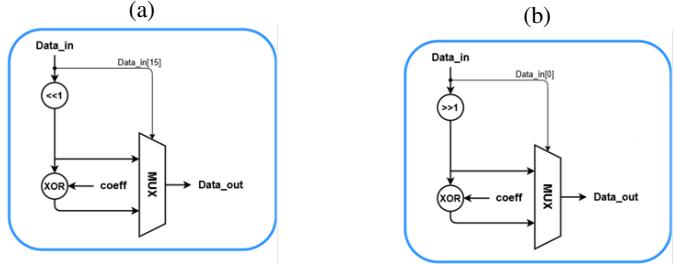


Fig. 2: Internal architecture of $\alpha, \beta, \alpha^{-1}$, and β^{-1} : (a) α, β : these are mul_x structures with coefficients $0 \times 990f$ and $0 \times c963$ for α and β respectively; (b) α^{-1} , and β^{-1} : these are $mul_x_inverse$ structures with coefficients $0 \times cc87$ and $0 \times e4b1$ for α^{-1} and β^{-1} , respectively.

eight times, refreshing 256 bits of the state. Taps T_1 and T_2 are extracted from updated LFSR segments to feed the FSM.

- 2) **FSM:** Consists of three 128-bit registers (R_1, R_2, R_3) and generates a 128-bit keystream per update. It uses taps T_1 and T_2 , two fixed-key AES rounds ($C_1 = C_2 = 0^{128}$), modular addition \oplus on 32-bit subwords, and AES transformations. The LFSRs update eight times before each FSM update to ensure fresh inputs.

SNOW-V employs a 256-bit key and 128-bit IV, and its use of SIMD-based vector operations enables high-speed software implementations. However, side-channel vulnerabilities remain a concern in embedded platforms.

$$\sigma = [0, 4, 8, 12, 1, 5, 9, 13, 2, 6, 10, 14, 3, 7, 11, 15] \quad (1)$$

The σ permutation maps byte i to its new position (byte 0 \rightarrow pos 0, byte 4 \rightarrow pos 1, etc.), implementing a column-wise transposition of the AES state matrix.

C. Profiling-based ML SCA Using LDA

Profiling SCA utilizes machine learning techniques to exploit power consumption patterns for key recovery. LDA is effective for this task, reducing dimensionality while preserving key-dependent class separability. Compared to CPA, LDA is more robust to noise and often requires fewer traces [12]. While used in prior SCA research, its application to SNOW-V is largely unexplored. Here, we employ a purely LDA-based profiling approach for bitwise key recovery, starting from the least significant bits and progressively reconstructing the full key.

D. Deep Learning-Based SCA Using FCN

To improve profiling performance, we also employ FCN, which can model complex non-linear relationships in power trace data [13]. Traces are first processed with Principal Component Analysis (PCA) to reduce dimensionality and noise. Using an identity model for labeling [13], the FCN consistently outperforms LDA, especially in recovering multiple bits together, showing a strong generalization for single-trace recovery. This demonstrates the practicality of deep learning-based SCA on SNOW-V.

LFSR A	$A_1, A_2, \dots, A_6, A_7, A_8, A_9, \dots, A_{14}, A_{15}$
Initial Value	$IV_0, IV_1, \dots, IV_6, IV_7, K_{00}, K_{01}, \dots, K_{06}, K_{07}$
LFSR B	$B_0, B_1, B_2, \dots, B_6, B_7, B_8, B_9, \dots, B_{14}, B_{15}$
Initial Value	$0x0, 0x0, \dots, 0x0, 0x0, K_{08}, K_{09}, \dots, K_{14}, K_{15}$

TABLE I: Initialisation of LFSR: LFSR A is half filled with the entire 128-bit IV and the other half with the first half of the 256-bit key. LFSR B is half filled with the remaining part of the key and the other half with zeros.

III. ATTACK METHODOLOGY

A. Initial Findings

Our analysis of SNOW-V reveals potential SCA attack targets:

- **LFSR:** Stores the secret key and IV during initialization, making it the most susceptible component.
- **FSM Transitions:** State changes may leak key-related information.
- **Field Multiplication (mul_x):** Certain key scheduling operations may contribute to leakage. The internal structure is shown in fig. 2.

During initialization, the LFSR holds the complete key and IV, while the FSM registers and AES round keys (C1, C2) are set to zero. Consequently, the AES unit does not exhibit key-dependent leakage, serving only to scramble the output stream.

According to the SNOW-V specification [1], the initialization process follows the mappings shown in table I.

Here, the secret key K is represented as $(k_{15}, k_{14}, \dots, k_1, k_0)$ while the IV is given by $(iv_7, iv_6, \dots, iv_1, iv_0)$. Each key byte k_i and IV byte iv_j (for $0 \leq i \leq 15$ and $0 \leq j \leq 7$) consists of a 16-bit value.

These equations indicate that the LFSR, particularly the sections holding the key, is a critical attack target.

B. Strategy for Side Channel Attack on SNOW-V

The LFSRs serve as the primary target for key extraction due to their role in storing the 256-bit secret key. In the initialization state, the most significant 128 bits are stored in LFSR B ($b[15] \text{--} b[8]$) and the least significant 128 bits in LFSR A ($a[15] \text{--} a[8]$). The known 128-bit IV is loaded into LFSR A ($a[7] \text{--} a[0]$), while the lower half of LFSR B is set to zero, as shown in table I.

Before entering the FSM stage, the LFSRs perform eight update iterations. We focus on the update functions for registers $a[15]$ and $b[15]$, expressed as:

$$u = mul_x(A[0], 0x990f) \oplus A[1] \oplus mul_x^{inv}(A[8], 0xcc87) \oplus B[0]$$

$$v = mul_x(B[0], 0xc963) \oplus B[3] \oplus mul_x^{inv}(B[8], 0xe4b1) \oplus A[0]$$

In the first iteration, u depends on $A[0]$, $A[1]$, $A[8]$, and $B[0]$. Since $A[0]$, $A[1]$, and $B[0]$ are known, $A[8]$ can be directly recovered [3]. This process is repeated for u and v in subsequent iterations, each time revealing new key-related LFSR blocks. By systematically applying this method, all segments of the secret key can be extracted.

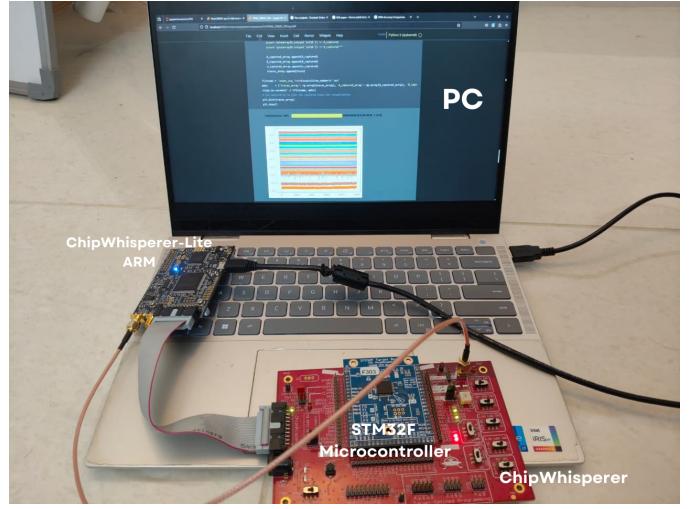


Fig. 3: Hardware setup showing workstation, ChipWhisperer capture and target boards, and an STM32 embedded board mounted on the target board and connected via cables. The STM32 microcontroller operates at a clock frequency of 7.37 MHz and sampling rate is four times the clock frequency.

C. Attack Algorithms

The SCA begins with a **TVLA** [14] using 100,000 power traces captured under fixed and random IV conditions to identify the potential source of the leakage within the algorithm. Leakage points are identified where the absolute t -value exceeds 4.5 [14], confirming exploitable data-dependent leakage.

Two profiling attack techniques are applied:

- **LDA-Based Attack:** Supervised LDA models are trained on traces labeled with the last 1, 2, 4, or 8 bits of the target key byte. LDA reduces dimensionality while maximizing class separability. The training and testing set is split as 80:20, and performance is evaluated with 10,000, 50,000, and 100,000 training traces as discussed in Section IV.
- **FCN-Based Attack:** FCN model the non-linear relationship between leakage and key values. Power traces are preprocessed using PCA to the top 2,000 components (preserving 99% variance) and Known Value Correlation (KVC) to isolate highly key-dependent segments, typically during early LFSR updates. The FCN architecture has three dense hidden layers (512, 256, 128 neurons) with ReLU, LeakyReLU, PReLU, ELU, or SELU activations, followed by a softmax output layer. Models are trained for 100 epochs on the PCA-reduced, KVC-filtered dataset, achieving high accuracy in multi-bit key recovery as discussed in the upcoming section.

IV. EXPERIMENTAL RESULTS

To assess the effectiveness of profiling side-channel attacks on the SNOW-V stream cipher, we evaluated two machine learning-based classifiers: **LDA** and **FCN**. The experiments were conducted using power traces captured from an STM32

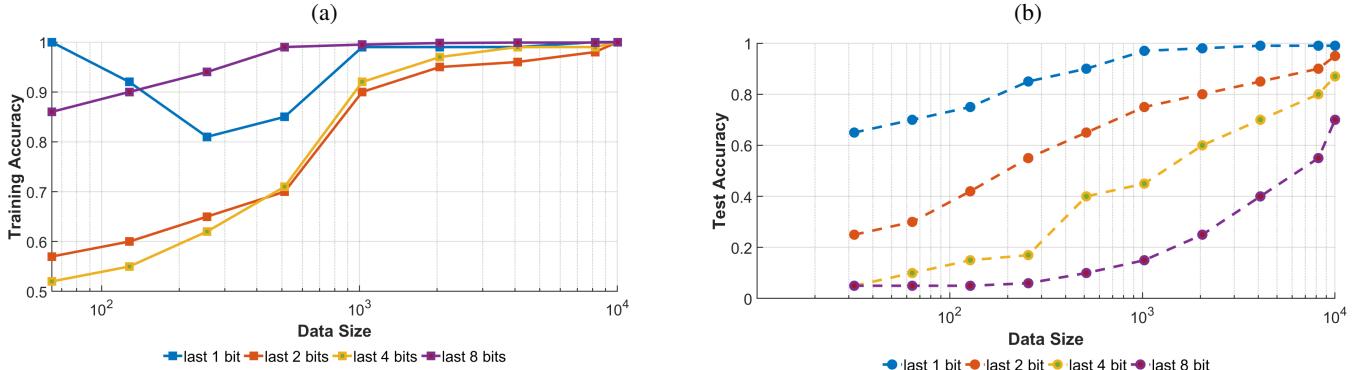


Fig. 4: LDA classification accuracy for recovering bits of the internal state word $A[8]$ across varying data sizes with a 64:16:20 training-validation-testing split. (a) Training accuracy for the last n bits ($n = 1, 2, 4, 8$), showing improvement as training traces increase. (b) Test accuracy for the last n bits, demonstrating reliable recovery even for 8-bit cases with increasing traces.

microcontroller as shown in fig. 3, with the goal of recovering the last 1, 2, 4, and 8 bits of a target key byte.

A. LDA-Based Classification

LDA showed strong performance in low-dimensional classification tasks. The training and testing accuracy are shown in fig. 4. For the 1-bit recovery scenario, it achieved an accuracy of approximately **99%**, and for 2-bit recovery, accuracy ranged between **90% and 95%**. However, as the number of target key bits increased, classification accuracy declined. For the 8-bit recovery task, the accuracy dropped to around **60%**, indicating LDA's limited capacity to handle complex or non-linear leakage. Fig. 4 further shows that LDA achieves over **90%** accuracy for 1- and 2-bit recovery with as few as 1,000 traces, while 4- and 8-bit recovery require larger datasets. With 100,000 traces, the model exceeds **95%** accuracy even for 8-bit classification of $A[8]$. To improve the attack success in such cases, **majority voting** across multiple traces was applied [13], which provided some improvement but did not fully compensate for the underlying limitations.

B. FCN-Based Classification

The FCN-based approach significantly outperformed LDA across all bit-recovery configurations. The accuracies across different layers and the corresponding bit recovery configurations are presented in fig. 5. For 1-bit classification as shown in fig. 5a, the FCN achieved near-perfect accuracy ($\sim 100\%$), and it maintained high accuracy even in the more challenging 8-bit scenario ($\sim 80\%$) in fig. 5d. This demonstrates the FCN's ability to learn non-linear relationships and extract meaningful features from high-dimensional trace data without requiring manual feature selection. Despite the increased computational cost and training time, the FCN provided more robust and consistent results across all test cases. Furthermore, the effect of PCA was analyzed by training FCN models with and without dimensionality reduction. For 1-bit recovery in fig. 5a, PCA had a negligible impact, with both models achieving $\sim 100\%$ accuracy. However, as recovery complexity increased, PCA-based models consistently outperformed non-PCA ones. For 2-bit recovery in fig. 5b, PCA improved

TABLE II: Accuracy (%) with FCN without using PCA for Different Bit Levels and Activation Functions

Activation Function	1-bit		2-bit		4-bit		8-bit	
	Train	Test	Train	Test	Train	Test	Train	Test
ReLU	100	100	83	83	26	26	6	5
LeakyReLU	100	100	82	82	49	49	5	5
PReLU	100	100	69	69	49	49	6	5
ELU	100	100	87	87	6	6	0	0
SELU	100	100	88	88	57	57	0	0
Swish	100	100	81	80	44	43	0	0
Mish	100	100	83	83	45	45	0	0

accuracy from around **85%** (non-PCA) to **95%**, while for 4-bit recovery fig. 5c it boosted accuracy from nearly **50%** to above **75%**. Most notably, in the 8-bit case fig. 5d, PCA-based models retained about **80%** accuracy, whereas non-PCA models dropped below **10%**. These results highlight the critical role of dimensionality reduction in stabilizing FCN performance for higher-bit recovery.

C. Impact of PCA on FCN Performance

We further evaluated the performance of FCN without and with **(PCA)** applied to the input traces, as shown in table II and table III. PCA was used to retain **99% of the total variance**, significantly reducing the dimensionality of the input features. This dimensionality reduction led to notable improvements in classification accuracy, particularly in higher-bit recovery tasks. For the 8-bit classification, the use of PCA improved the accuracy, reduced training time, and helped mitigate overfitting by filtering out noisy or irrelevant components from the trace data. The improvement is most evident in the accuracy trends shown in the performance plots, where PCA-enhanced FCN models consistently outperform their non-PCA counterparts.

D. Comparison of LDA vs FCN+PCA attack models on SNOW-V

We explored two profiling attack strategies: LDA and FCN. LDA demonstrated effectiveness in low-bit width recovery scenarios, enabling step-by-step key reconstruction. FCN, on

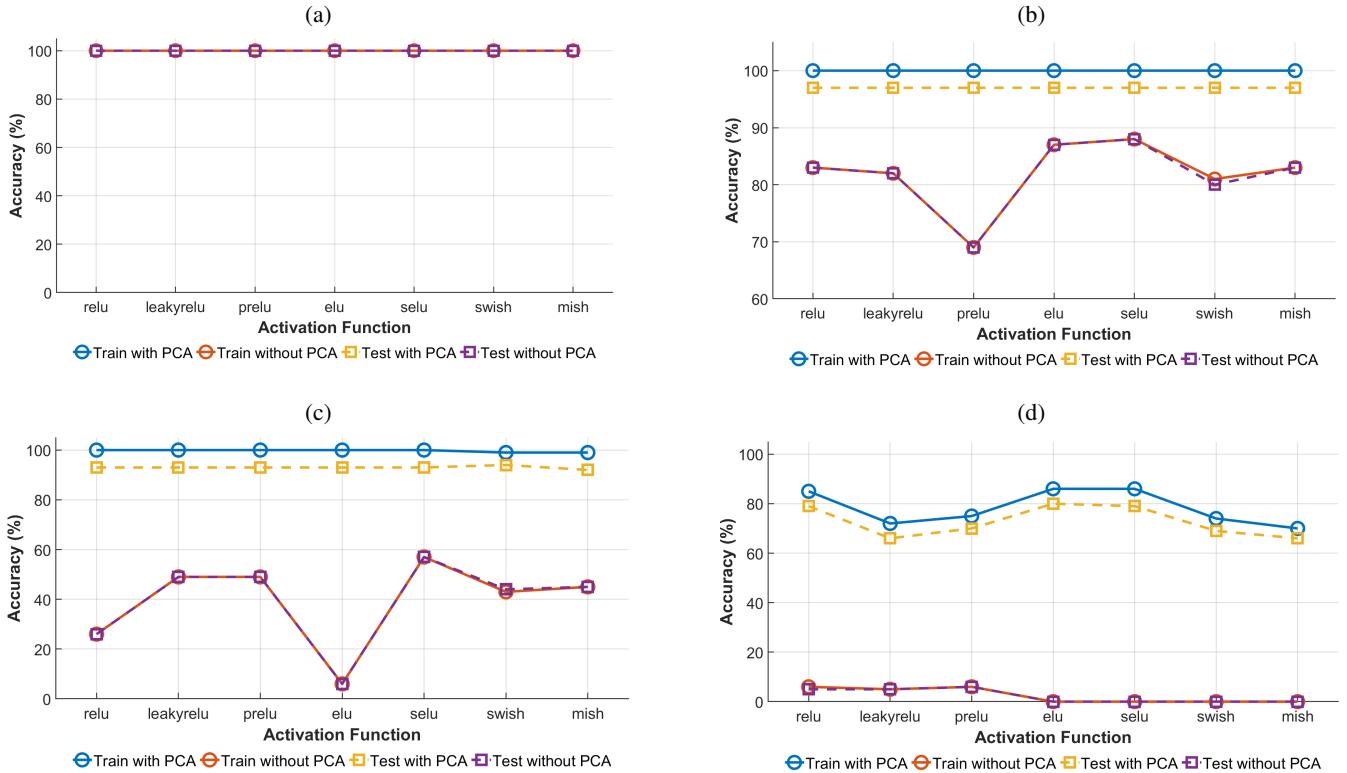


Fig. 5: Accuracy of bit recovery for the internal state word $A[8]$ using a FCN trained on 10^5 traces, with and without PCA (80:20 train–test split). (a) 1-bit recovery shows negligible PCA impact; (b) 2-bit recovery improves with PCA, especially for PReLU layers; (c) 4-bit recovery drops overall, but PCA gives up to 15% gain; (d) 8-bit recovery falls sharply, with non-PCA models under 10%.

TABLE III: Accuracy (%) using FCN + PCA for Different Bit Levels and Activation Functions

Activation Function	1-bit		2-bit		4-bit		8-bit	
	Train	Test	Train	Test	Train	Test	Train	Test
ReLU	100	100	100	97	100	93	85	79
LeakyReLU	100	100	100	97	100	93	72	66
PReLU	100	100	100	97	100	93	75	70
ELU	100	100	100	97	100	93	86	80
SELU	100	100	100	97	100	93	86	79
Swish	100	100	100	97	99	94	74	69
Mish	100	100	100	97	99	92	70	66

TABLE IV: LDA Classification Accuracy for Different Power Traces

	10,000 Traces	50,000 Traces	100,000 Traces
Last bit of Key	0.9995	1.0	1.0
Last 2 bits of Key	0.815	0.8965	0.95095
Last 4 bits of Key	0.451	0.6841	0.84815
Last 8 bits of Key	0.102	0.3431	0.57455

the other hand, proved significantly more powerful by capturing complex, non-linear leakage characteristics, thereby achieving higher accuracy across multiple bit widths. We further assessed different activation functions, namely ReLU, Leaky ReLU, PReLU, SELU, and ELU. SELU and ELU

TABLE V: Comparison of Profiling Attacks (LDA vs PCA + FCN) with n bit Accuracy, where $n = 1, 2, 4$, and 8

Aspect	LDA	PCA + FCN
Attack Type	Profiling	Profiling (deep learning)
Performance		
1-bit key	High Accuracy ($\approx 99\%$)	Perfect Accuracy ($\approx 100\%$)
2-bit key	Good Accuracy ($\approx 90\text{--}95\%$)	High Accuracy ($\approx 97\text{--}99\%$)
4-bit key	Good Accuracy ($\approx 70\text{--}80\%$)	Good Accuracy ($\approx 90\%$)
8-bit key	Fair Accuracy ($\approx 60\%$)	Good Accuracy ($\approx 80\%$)
Complexity	Low	High

consistently achieved the highest accuracy, likely due to their negative and zero-centered activations, which allow the network to better capture subtle trace variations indicative of key leakage [15]. ReLU delivered moderate performance, benefiting from suppression of noisy negative values but also discarding potentially informative leakage below zero. Leaky ReLU yielded the lowest accuracy, as its linear negative slope tends to preserve noise, reducing the model’s ability to isolate key-dependent features. To achieve high SCA attack success, we performed a majority vote for a given number of traces, as shown in fig. 6.

To further contextualize our results, we present a bar graph comparing the three approaches—CPA+LDA, LDA-only, and FCN—as shown in fig. 7. Recovering 8 bits of the secret key

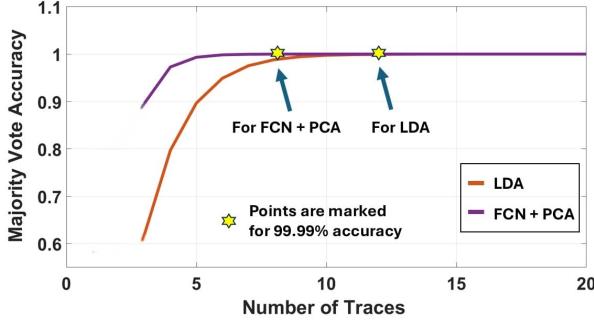


Fig. 6: Majority-vote accuracy as a function of the number of traces for: LDA-based analysis and FCN with PCA. Accuracy probability is computed using the majority-voting formula described in [13]. The plot shows LDA requires 12 traces, whereas FCN assisted with PCA requires only 8 traces for 99.99% for majority voting-based accuracy.

requires 50 traces with CPA+LDA, 12 traces with LDA, and only 8 traces with FCN combined with PCA, highlighting the superior efficiency of the FCN-based approach. Although FCN entails the highest training complexity, it achieves the best performance across all evaluation metrics with the fewest traces. This trade-off underscores the growing relevance of deep learning in side-channel analysis: the increased computational cost during training is offset by significant gains in trace efficiency and accuracy.

While this study demonstrates a machine learning-based power side-channel attack on the SNOW-V cipher implemented on an STM32 microcontroller using the ChipWhisperer platform, the methodology is broadly applicable to other platforms, devices, and cryptographic algorithms. The core principle—profiling power traces with machine learning models such as LDA and FCN—is independent of the specific hardware or algorithm. By identifying key-dependent leakage points in any target implementation and making minor adjustments to model parameters and preprocessing, this attack approach can be effectively adapted to a wide range of cryptographic algorithms.

V. DISCUSSIONS & CONCLUSION

In this paper, we presented a fully machine learning-based power SCA attack on the SNOW-V stream cipher. A TVLA was first conducted to confirm the presence of data-dependent leakage in the SNOW-V implementation on an STM32 microcontroller.

Compared to the previous work [2], which primarily relied on CPA combined with LDA, the current study introduces a more robust, model-agnostic methodology. While CPA+LDA (prior work) required a significantly higher number of traces (~ 50) and was sensitive to power model accuracy, our proposed FCN+PCA-based approach eliminates this dependency with lower MTD (~ 8), offering improved generalization in practical attack scenarios and demonstrating this using measured data on the SNOW-V running on the 32-bit ARM microcontroller.

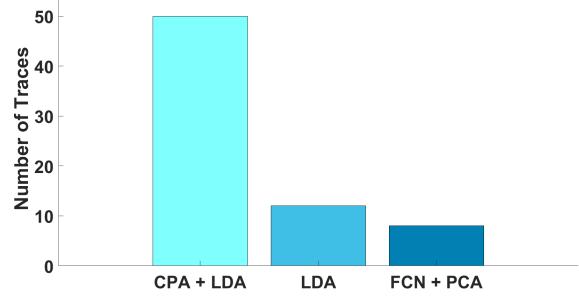


Fig. 7: Minimum number of traces required to achieve 99.99% SCA attack accuracy in recovering the correct key for SNOW-V using three attack methods - CPA+LDA (prior work [2]), proposed LDA, and FCN+PCA.

Overall, our findings not only validate the vulnerability of SNOW-V to advanced profiling attacks but also highlight the need for robust countermeasures such as masking. Future work could investigate advanced neural architectures, automated feature selection techniques, and more extensive resilience testing across diverse leakage scenarios.

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