# Side-Channel and Fault Attack Testing in the age of AI


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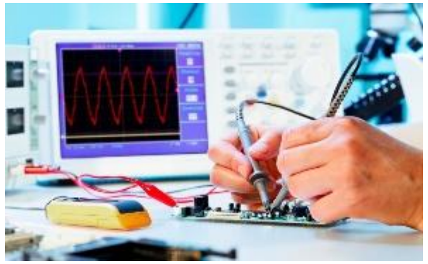
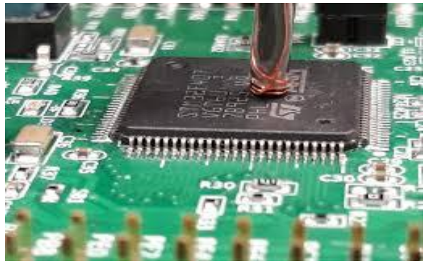
# **Artificial Intelligence:** Boon for Security Evaluations of Cryptosystems

Targets insecure real-life implementation of provably secure cryptographic encryption







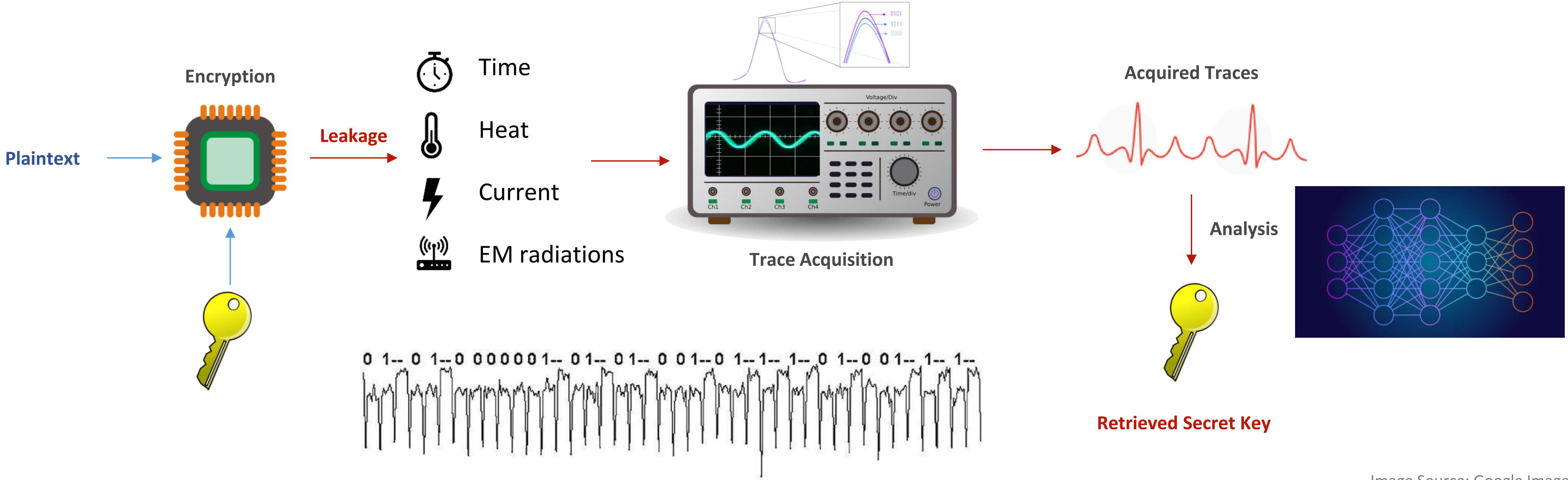

**AI for Attacks**

- Can be used to attack cryptographic implementation using side-channel information
  - More *efficient* than standard statistical techniques
  - Can even *break efficient side-channel countermeasure* implementation like masking
- Can be used to evaluate fault attack countermeasures
  - *Aids to mount efficient fault attacks* on cryptographic implementation

Image Source: Google Images

# This Talk

(Our experience with) **Challenges and Future of Machine Learning in SCA**

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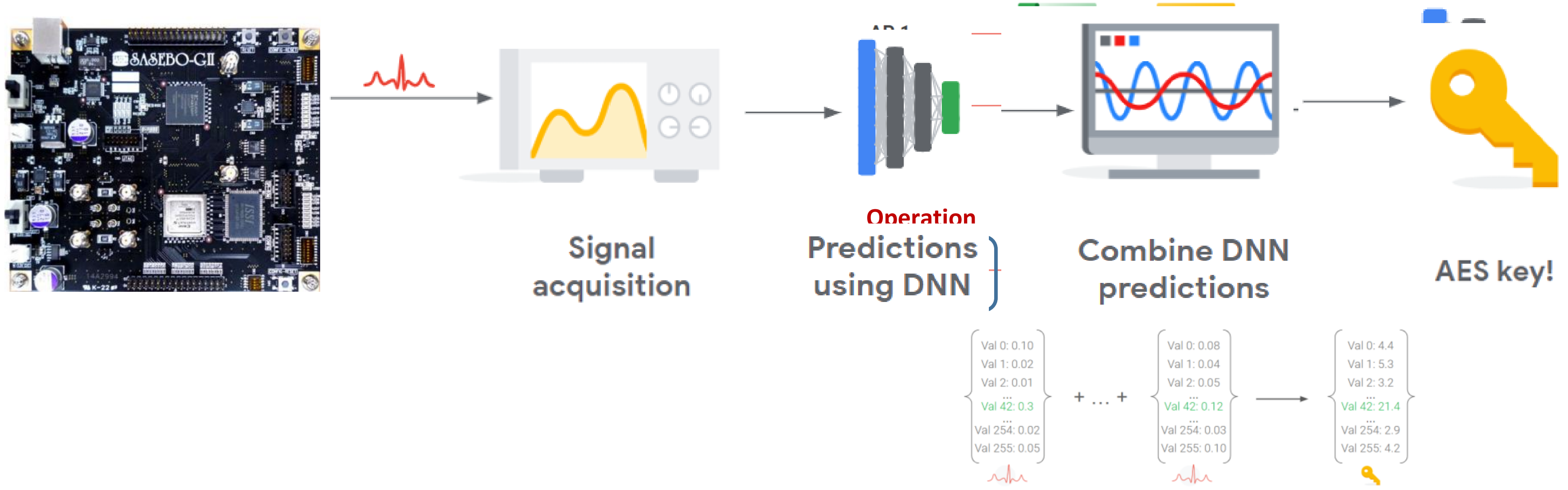
# **Profiled Deep Learning** based Attack

## Advantage of Deep Learning Approach

- Template attacks (profiled attacks) are based on the Gaussian Assumption of the leakage distribution
  - Deep Learning-based approach relaxes the Gaussian Assumption
- The acquired traces do not require any types of pre-processing (like trace synchronization, denoising, feature selection, feature extraction, etc.)
- The deep learning model can combine multiple leakage points
  - Works efficiently against masking-based countermeasures than classical statistical methods

Unknown Key




Profiling Phase

Attack Phase

H. Maghrebi et al., "Breaking cryptographic implementations using deep learning techniques." SPACE 2016

# AI for Implementation Security : The Way Forward

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- **Lack of documentation for AI specific pitfalls in implementation security context**

    - How to pre-process data (like side-channel traces) to render them training friendly ?
    - How to avoid overfitting ?
    - Which architectures to use for what use-cases? **Is deep = better?**
    - How to ensure quality of training data? Issues like class imbalance, requisite amount of data.
    - Is the inference result interpretation reliable (like high accuracy, but on unbalanced data) ?
    - Statistical tests (like CPA) are inherently portable. But what about ML models?

Not all implementation security engineers may know ML internals/details to take decisional calls on these issues

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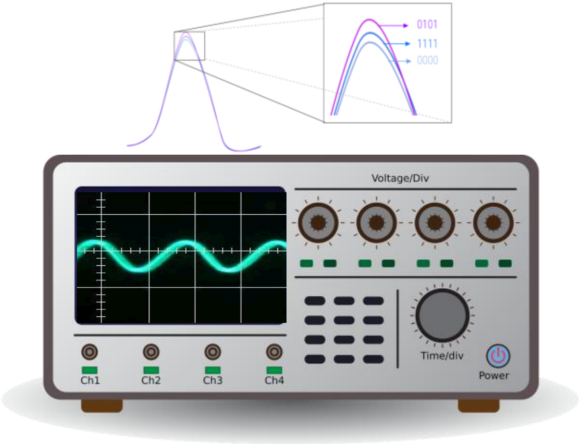


**Long traces in SCA**
Few informative sample points in the trace


[1] Hajra, Suvadeep, et al. "On the instability of softmax attention-based deep learning models in side-channel analysis." Ieee transactions on information forensics and security 19 (2023): 514-528.

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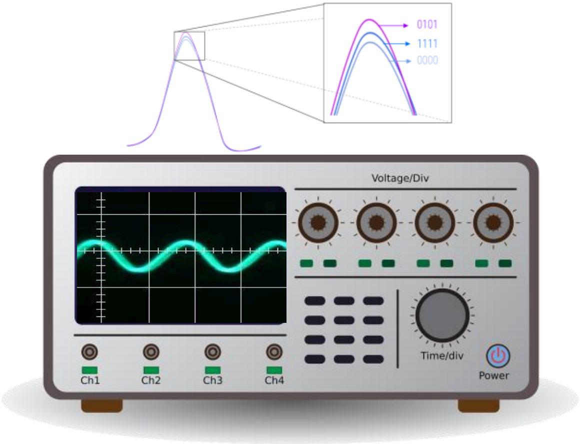


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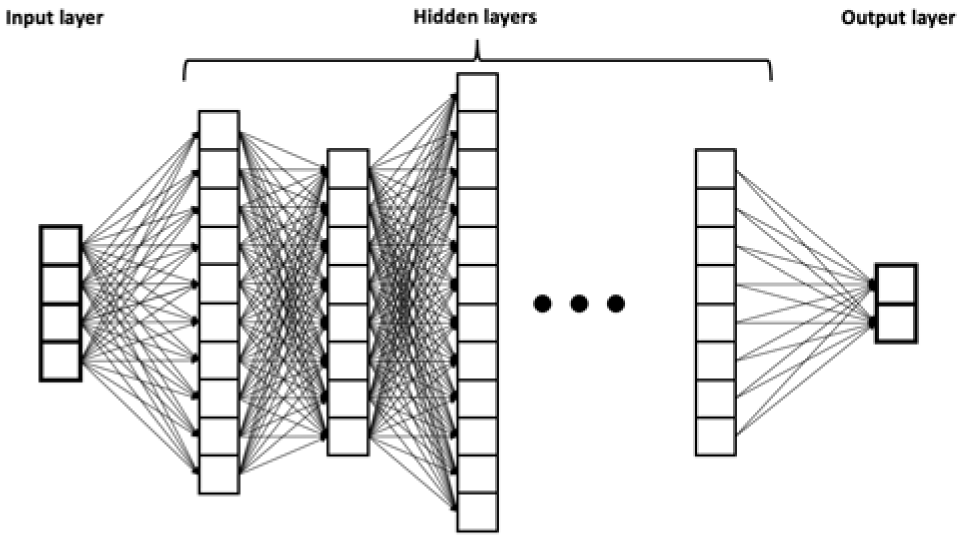


**Attack using Convolutional Neural Network**


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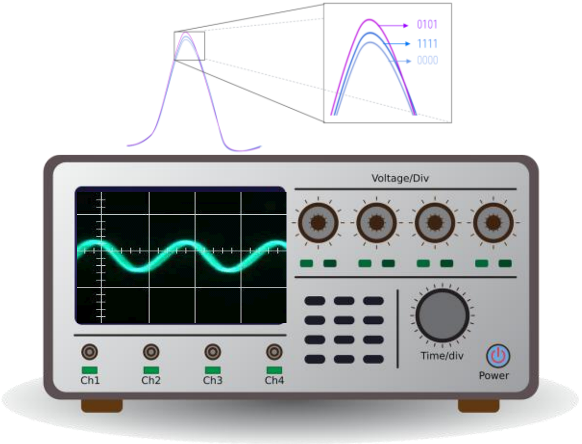


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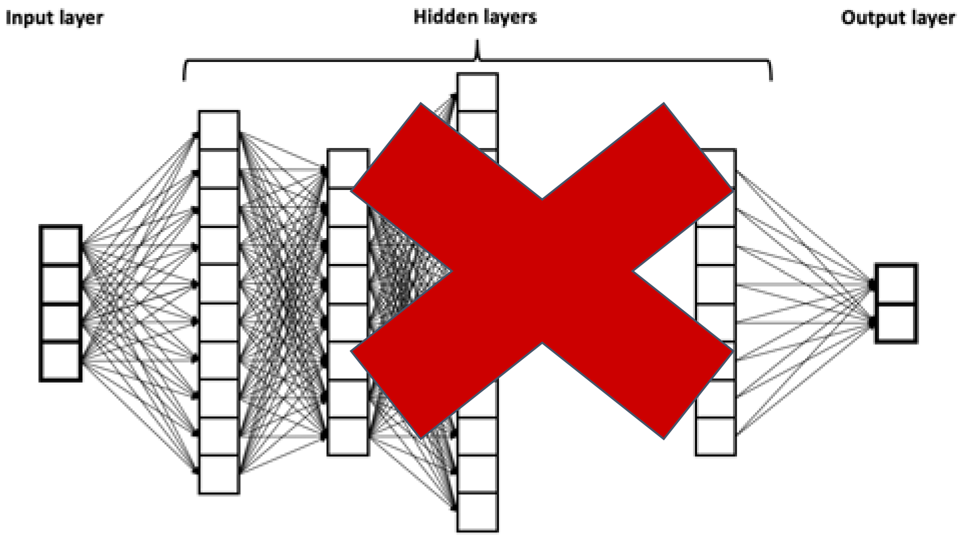


**Attack using Convolutional Neural Network**

Pitfall!!! High gradient for softmax; Highly non-smooth loss surface; unstable learning

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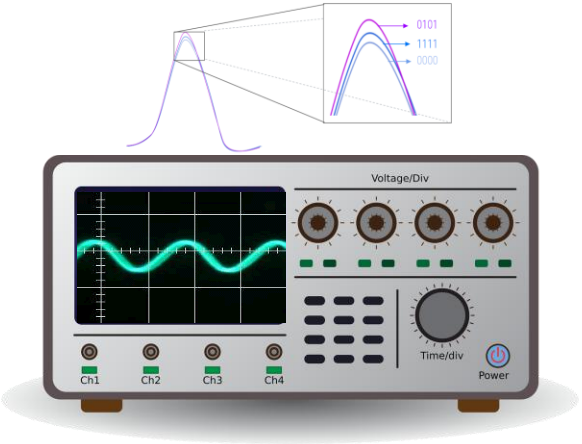


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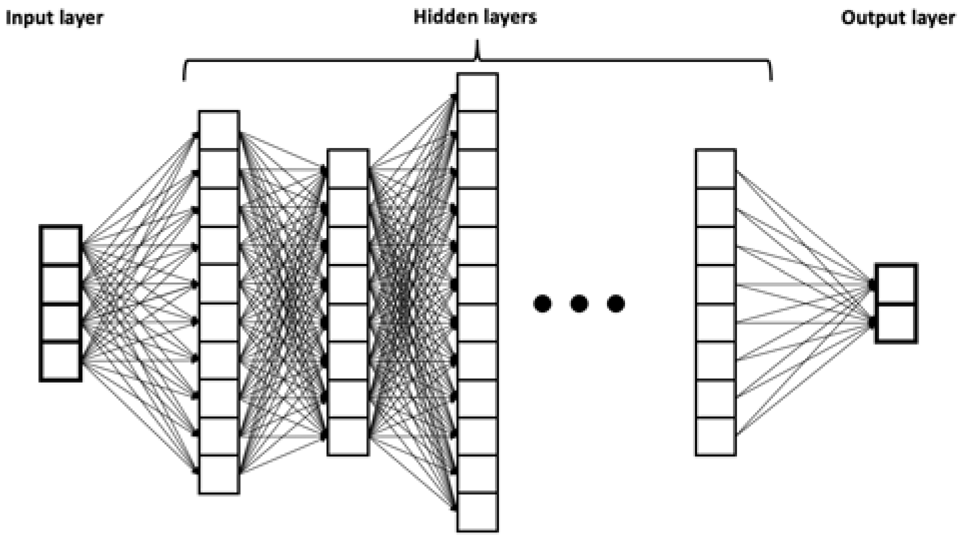


**Attack using Convolutional Neural Network**

Fix: Machine Learning specific fixes (multi-head softmax) for accurate SCA using CNNs


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  - Statistical tests (like CPA) are inherently portable. But what about ML models?

Not all implementation security engineers may know ML internals/details to take decisional calls on these issues

**Way Forward:**

- Document problems with vanilla ML approaches (i.e. what *does not* work) for dissemination.
- Foster community dialogue at the intersection of SCA and Machine Learning
- Develop whitepapers and RFC documents to answer some of the questions raised here

# AI for Implementation Security : The Way Forward

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- **Need for interdisciplinary know-how to *improve* implementation security testing through AI**
    - Are there problems in SCA whose counterparts exist in machine learning?
    - Does AI make certain SCA specific problems *easier* to solve?

Exploring the intersection of AI and SCA requires intricate intertwining of two completely different domains.

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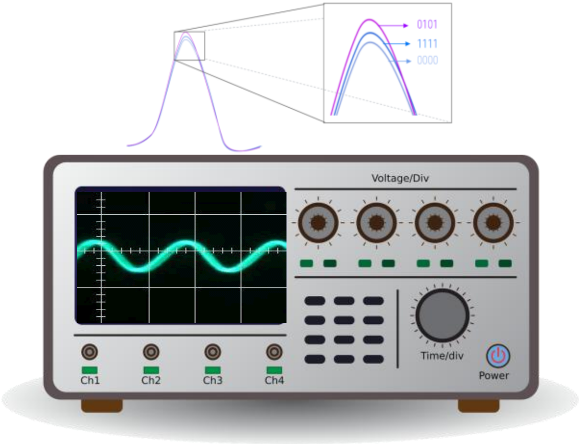


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→ **Mechanisms in machine learning capable of capturing long, temporal input semantics ?**

[1] Hajra, Suvadeep, Siddhartha Chowdhury, and Debdeep Mukhopadhyay. "Estranet: An efficient shift-invariant transformer network for side-channel analysis." IACR Transactions on Cryptographic Hardware and Embedded Systems 2024.1 (2024): 336-374.

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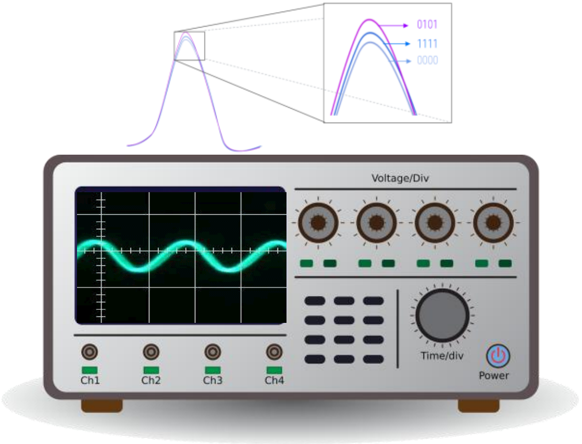


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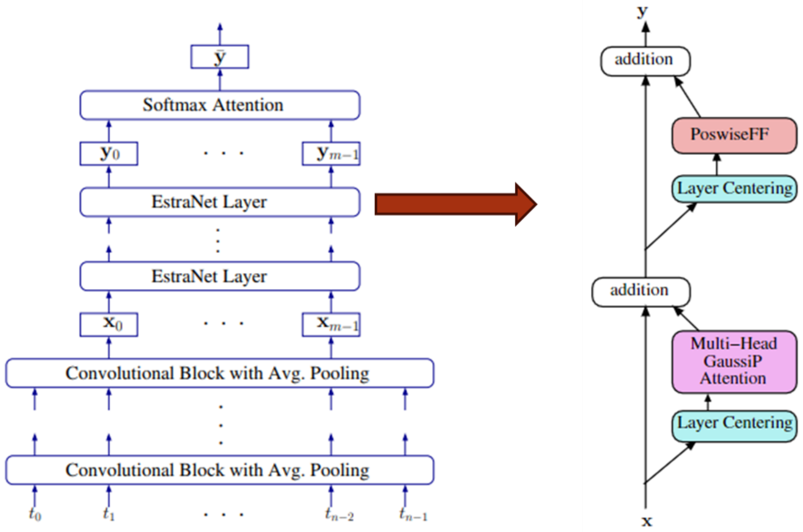


EstraNet : SCA specific architecture based on advances in ML specific techniques - new attention mechanisms (relative positional encoding) and layer normalization


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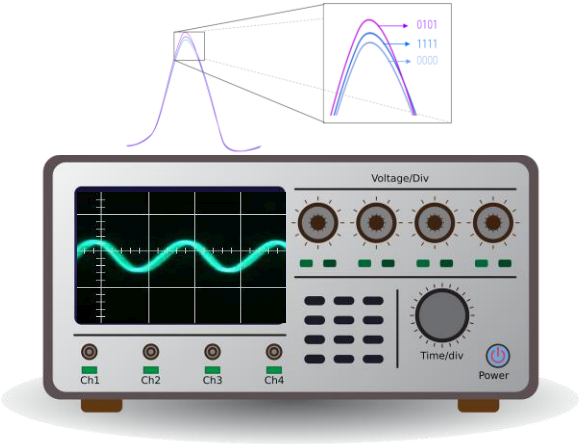


**Very Long traces in SCA**

EstraNet does not work beyond 40K features. What if the target implementation has > 40K features in side-channel trace?

**Mechanisms in machine learning for operating a "collection" of models in specific topologies?**

[2] Hajra, Suvadeep, Soumi Chatterjee, and Debdeep Mukhopadhyay. "UNIDLE: A Unified Framework for Deep Learning-based Side-channel Analysis." Cryptology ePrint Archive (2024).

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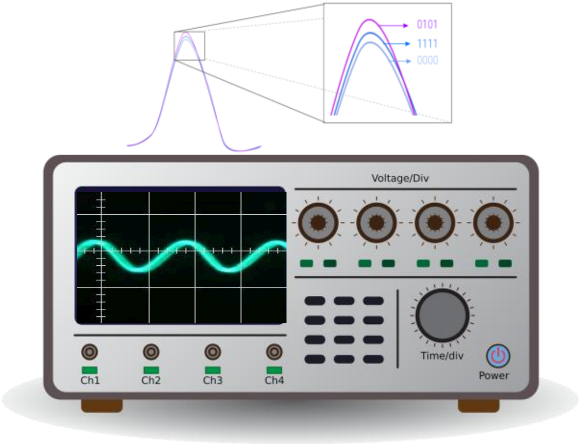


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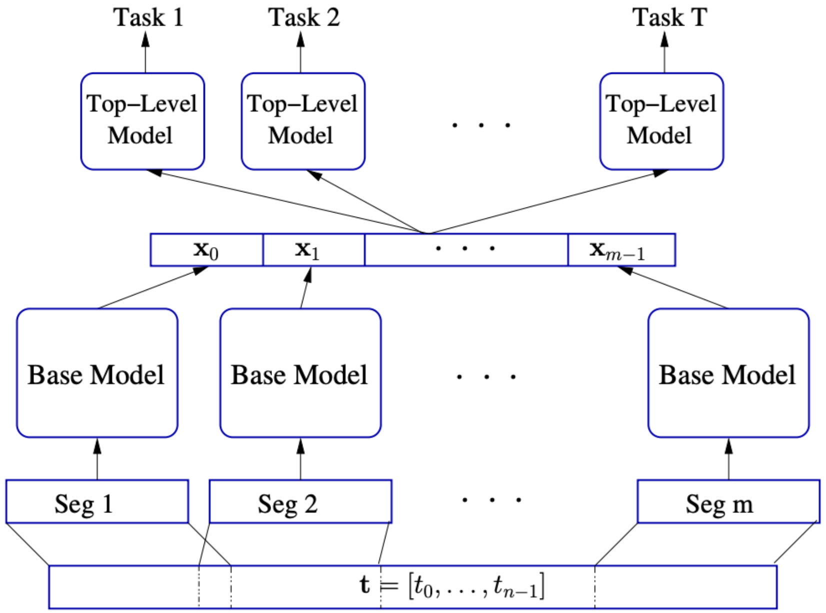


Exploits properties of interactions between ML models to construct a hierarchical topology of models (~100K features in SCA traces)


[2] Hajra, Suvadeep, Soumi Chatterjee, and Debdeep Mukhopadhyay. "UNIDLE: A Unified Framework for Deep Learning-based Side-channel Analysis." Cryptology ePrint Archive (2024).

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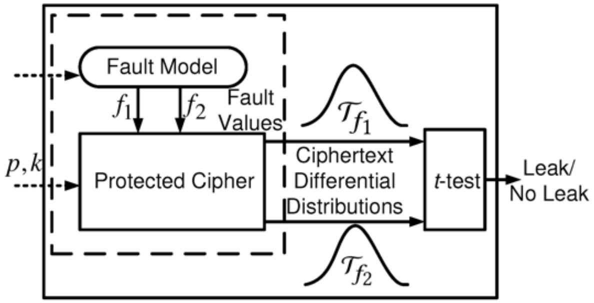


Automated Fault Analysis

Higher-order **t-test can only capture different statistical moments**, which has already been shown to be sub-optimal in the context of SCA leakages, even resulting in **false negatives**

**Can machine learning help build an automated test for multivariate inputs?**


[3] Saha, Sayandeep, et al. "Learn from your faults: leakage assessment in fault attacks using deep learning." Journal of Cryptology 36.3 (2023): 19.

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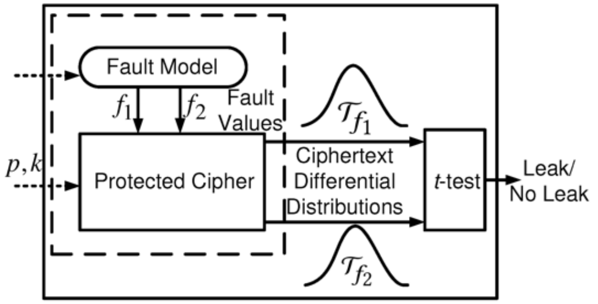


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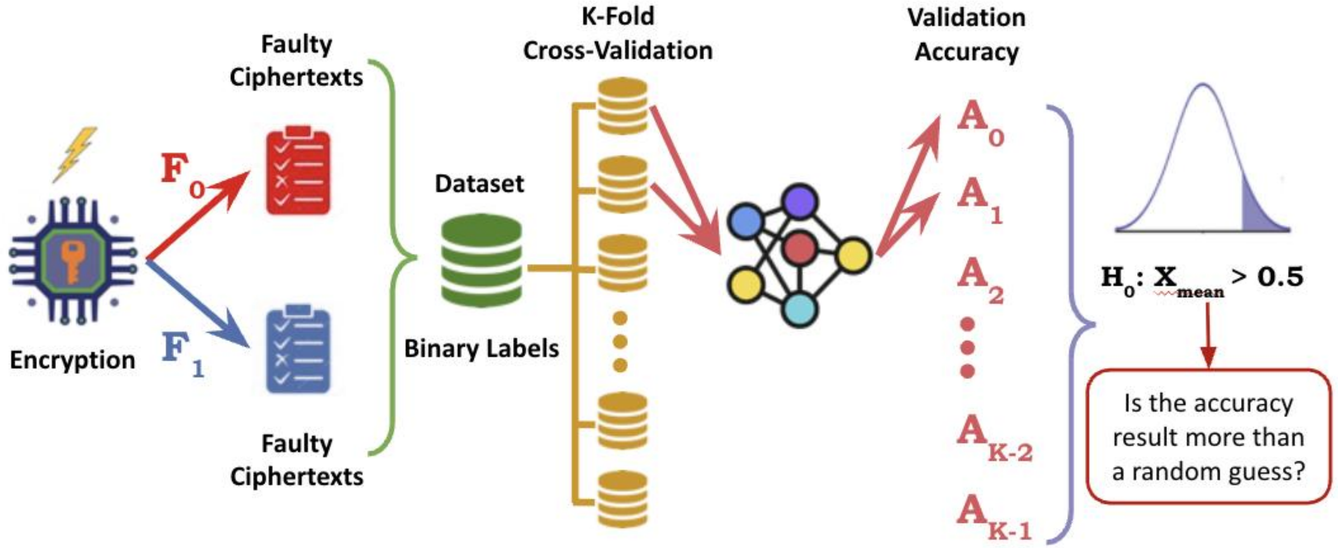


DL-FALAT : **Machine learning can learn highly multivariate functions and complex inter-relations between inputs**, implying an ideal candidate fault analysis automation.


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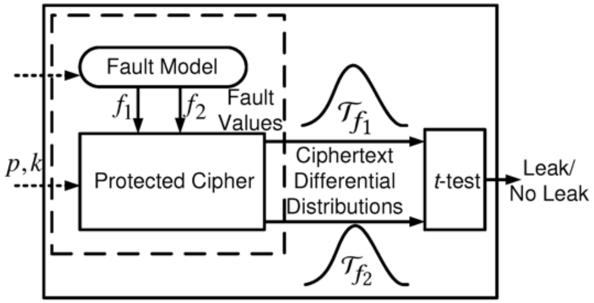


Automated Fault Analysis with unknown fault models

Even most ML based fault detection methods require functioning over *known* fault models. What about *unknown* models?

**Can learning agents be added to existing Machine Learning based fault automation?**


[4] Guo, Hao, et al. "ExploreFault: Identifying exploitable fault models in block ciphers with reinforcement learning." 2023 60th ACM/IEEE Design Automation Conference (DAC). IEEE, 2023.

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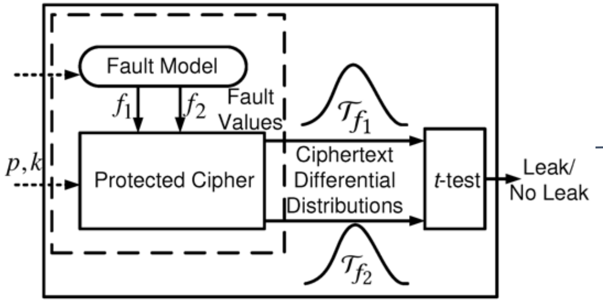


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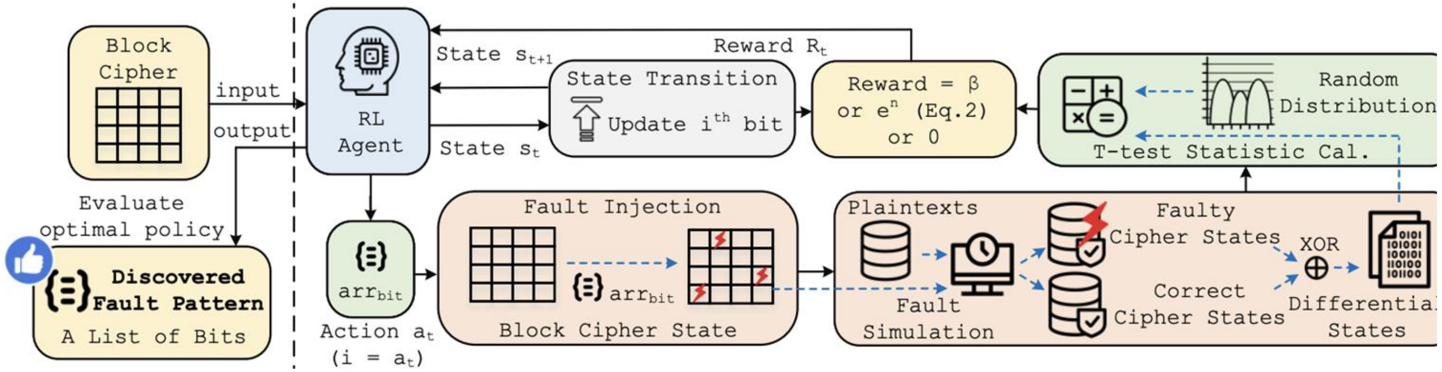


**Reinforcement Learning (RL) based Machine Learning pipeline** with active feedback loop for exploring newer, previously undiscovered fault models

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  - **Example**: [1], [2], [3], [4], [5]

Testing quality of entropy sources used in cryptosystem-under-test

Statistical Analyses is difficult (even NIST rolled back SP-800-22 for use for testing PRNGs in production level cryptosystems) ?

**Can properties of machine learning help in designing measures of entropy quality?**

[5] Pratihar, Kuheli, Rajat Subhra Chakraborty, and Debdeep Mukhopadhyay. "Latent RAGE: Randomness Assessment Using Generative Entropy Models." IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems 43.11 (2024): 3503-3514.

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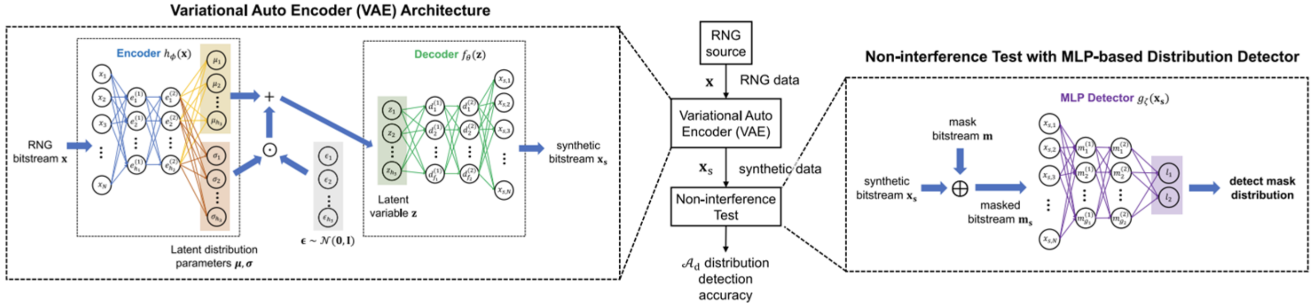


Use ML specific hypothesis - patterns are likely to occur on low-dimensional manifolds - to detect weak entropy sources by studying their projections to lower dimensional manifolds using Variational Auto-Encoders.


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Exploring the intersection of AI and SCA requires intricate intertwining of two completely different domains.

**Way Forward**:

- Explore more and more interdisciplinary solutions to problems in SCA
- Induct interdisciplinary experts, foster wider collaboration, and keep trying to find intersections in problems

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Pertinent questions facing the implementation security community for AI adoption:

- **Consensus on how we build upon each other’s research**
    - Statistical tests are algorithms; we publish the same, and anyone can use it.
    - Trained ML models + collected datasets are often considered as IPs. Not everyone open-sources them!
    - A **lack of consensus on how to share models/datasets will create isolated islands** in the implementation security community.

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- **Licensing**
  - What is the goodwill policy of licensing a model for testing *my* implementation, that had been partially trained on dataset curated by somebody else?
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Agreeing upon suitable licensing of ML in SCA research is crucial for the field to boom!

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As a lab, we try to open-source both source code (model architecture, hyperparameters) and datasets for the wider community to build upon.

- https://github.com/felu-mittir/DL_FALAT
- https://github.com/suvadeep-iitb/EstraNet

# AI for Implementation Security : The Way Forward

Pertinent questions facing the implementation security community for AI adoption:

- **Explainability and Democratization!**

  - Sophisticated toolings => use-cases limited to a small community of experts!
  - **Enabling wider adoption** of implementation security testing is paramount.
  - Apart from automation, **explainability** and **democratization** of our research goes a long way.

Constant efforts are needed on our part to engage non-experts in ML to adopt our workflows in their testing workflows.

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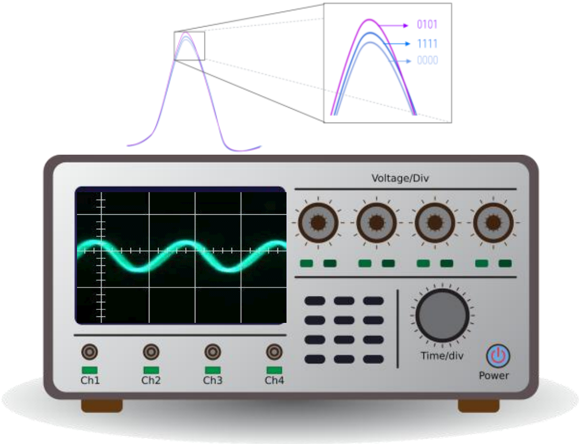
    - Explainability example : [1]




How does a security auditer explain even a successful audit by machine learning deployment?

Hard to know *why* a machine learning model makes the decision it does. And hard to capture SCA specific semantics in such contexts. Without a clearer understanding of how the model internally processes information, systematic improvements beyond trial-and-error become difficult

**Can a combination of (1) machine learning, (2) visualization techniques, and (3) statistics help with *explaining* SCA leakage in ML models?**

[1] Hajra, Suvadeep, and Debdeep Mukhopadhyay. "Black Box to Blueprint: Visualizing Leakage Propagation in Deep Learning Models for SCA." Cryptology ePrint Archive (2025).

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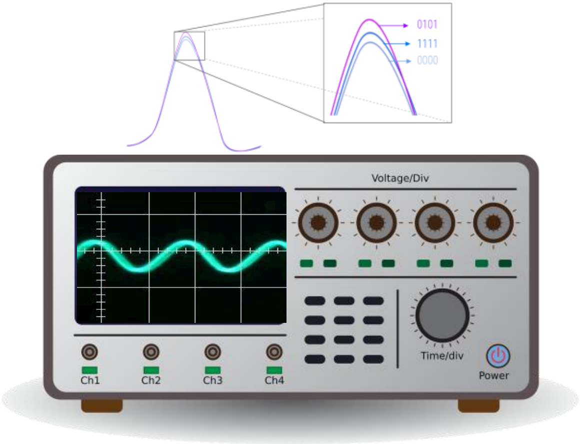


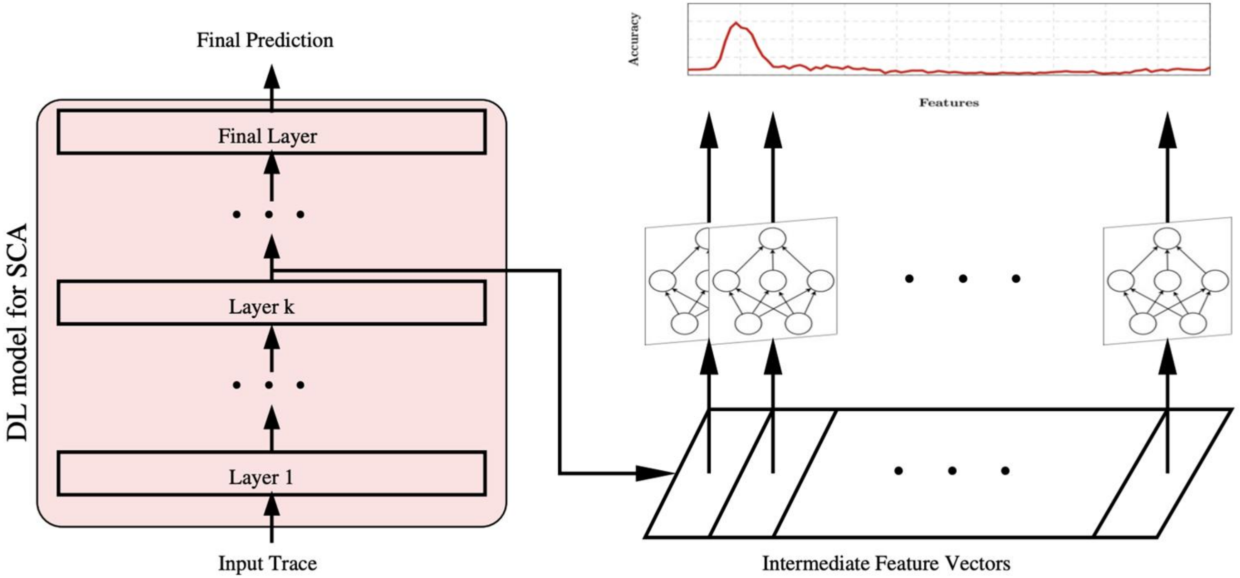


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Generalizable method to visualize flow of leakage while machine learning model processes SCA traces

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- **Explainability and Democratization!**
    - Explainability example : [1]
    - Democratization example: [2]


Given a framework for side-channel leakage assessment, how do we get a non-expert to use it?

**Can we use AI agents to automate and abstract out details of the framework?**

[2] Mandal, Upasana, et al. "µLAM: A LLM-Powered Assistant for Real-Time Micro-architectural Attack Detection and Mitigation." Proceedings of the 43rd IEEE/ACM International Conference on Computer-Aided Design. 2024.

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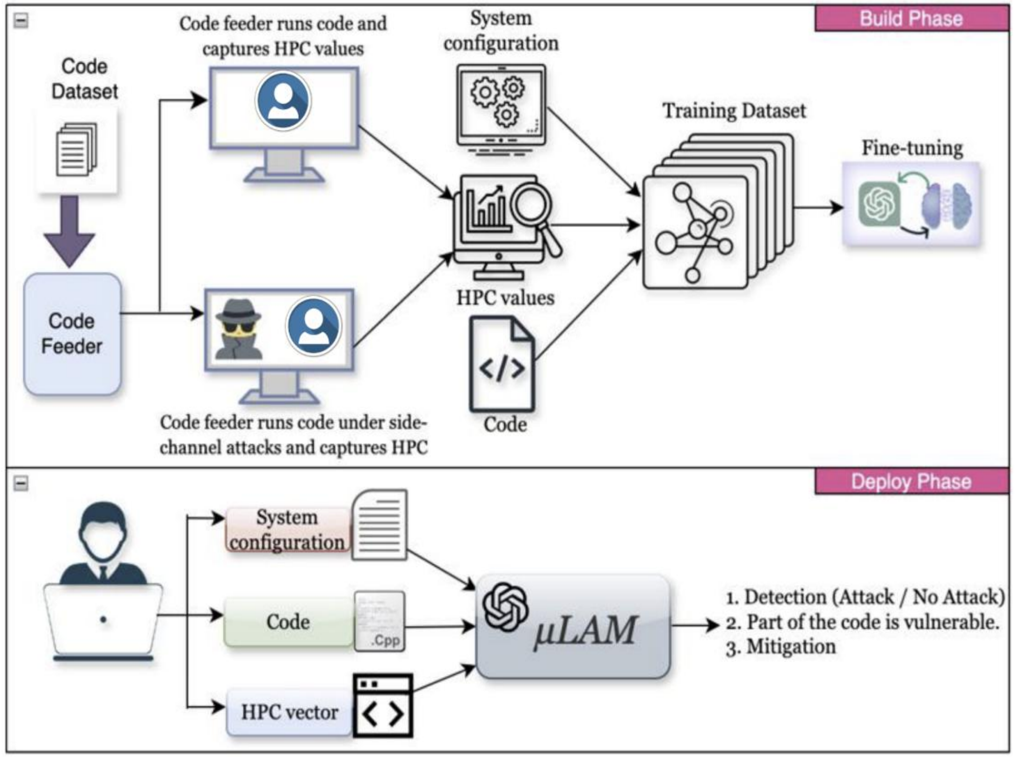


Design of a LLM based framework to abstract out details of internal side-channel leakage detection, to be used naturally by non-experts by simple English

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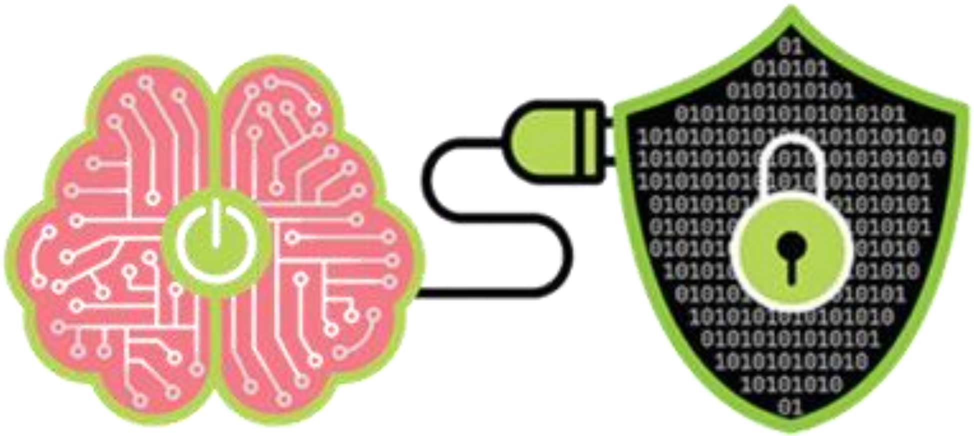
(Summary) Pertinent questions facing the implementation security community for AI adoption:

- **Lack of documentation for AI specific pitfalls in implementation security context**
- **Need for interdisciplinary know-how to improve implementation security testing through AI**
- **Consensus on how we build upon each other’s research**
- **Explainability and Democratization**

A big shout out to OPTIMIST in making inroads on taking steps in improving the quality and reproducibility of implementation testing!



# *Thank You*

For any query please feel free to contact

**Debdeep Mukhopadhyay**: debdeep.mukhopadhyay@gmail.com