Journal of Information Systems Engineering and Management
2025, 10(45s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Machine Learning Detects Stealthy Hardware Trojans via Side-Channel Analysis

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ARTICLE INFO

Received: 18 Dec 2024

Revised: 10 Feb 2025

Accepted: 28 Feb 2025

ABSTRACT

Hardware Trojans (HTs) pose a serious threat to integrated circuit (IC) security. Detection of HTs is extremely challenging due to their stealthy nature. Side-channel analysis techniques have emerged as promising approaches for HT detection by observing anomalies in physical parameters like power or delay. More recently, machine learning (ML) methods have been explored to enhance the accuracy and efficiency of side-channel based HT detection.

Background: This paper presents a novel approach using machine learning techniques to detect stealthy hardware Trojans through side-channel analysis. Hardware Trojans, malicious modifications inserted into integrated circuits during manufacturing, pose significant threats to the integrity and security of electronic systems. Traditional methods of detecting these Trojans often rely on known signatures or specific patterns, making them ineffective against subtle and sophisticated attacks.

Method: This paper provides a comprehensive review of research advancements in applying ML for side-channel based HT detection. First, an overview of HT attacks, their classification, threat models and detection challenges is presented. Next, various side-channel parameters like power, temperature, delay and electromagnetic emanations used for HT detection are discussed along with their merits and demerits. Furthermore, the application of supervised, unsupervised and semi-supervised ML algorithms for automated feature extraction and intelligent decision making is elucidated in detail.

Result: Specifically, the data collection strategies, feature extraction techniques, ML models and performance evaluation metrics adopted in existing literature are critically reviewed. In addition, the limitations of current approaches and promising future research directions like on-chip ML implementation, hierarchical ML and explainable ML models tailored for HT detection are highlighted.

Conclusion: Case studies on benchmark circuits are also presented to demonstrate the efficacy of ML-based side-channel HT detection methods. Through an extensive literature review and incisive analysis, this paper provides contemporary insights on the advancement of ML techniques to enable robust side-channel based HT detection for securing next-generation ICs.

Keywords: hardware trojans; side-channel analysis; machine learning; IC security

1. INTRODUCTION

Rapid technology scaling combined with globalization of the semiconductor industry has led to increased outsourcing of integrated circuits (ICs) design and manufacturing activities. This disaggregation of the IC supply chain has however raised concerns regarding insertion of malicious and surreptitious modifications termed as

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hardware Trojans (HTs) [1]. HTs can severely compromise the security of ICs deployed in critical systems spanning military, aerospace, financial, transportation, energy and medical domains [2]. For instance, an activated HT can cause denial of service, degrade performance, leak sensitive information or even trigger catastrophic damage to the host system. Owing to their stealthy nature and multitude of activation mechanisms, detection of hardware Trojans poses an extremely challenging problem.

Over the past decade, numerous approaches have been investigated by researchers worldwide for detecting hardware Trojans implemented at different stages of the IC development cycle. Broadly, these techniques can be classified into destructive, logic testing and side-channel analysis (SCA) based approaches [3]. Destructive and invasive methods like optical inspection, scanning electron microscopy etc. facilitate direct examination but incur significant time and cost overheads. Logic testing methods apply input patterns to trigger Trojans and observe erroneous responses. However, generation of test patterns to activate rare Trojans events is often infeasible due to exponentially increasing search space. In contrast, side-channel analysis relies on measuring circuit level characteristics or physical parameters that get impacted due to Trojan insertion [4]. Common side-channels utilized for HT detection include power consumption, path delays, temperature profile and electromagnetic (EM) emanations. Minor deviations observed in these characteristics indicate presence of Trojans in the test IC with respect to a golden reference. Side-channel analysis offers a promising solution for HT detection owing to its non-intrusiveness and high sensitivity to parametric variations induced by Trojans. At the same time, separation of Trojan effects from noise and process variations remains an open challenge.

Most traditional side-channel analysis techniques adopt manual feature extraction and thresholding based Trojan detection [5]. Such methods lack the capability to handle diverse Trojan parametric footprints across wide operating conditions. They also suffer from limited detection accuracy in noisy measurement environments. In order to overcome these challenges, machine learning (ML) approaches are being actively researched by the hardware security community over the past few years. ML offers intelligent algorithms that can automatically learn distinguishable patterns from large volumes of side-channel data. By statistical correlation of these complex patterns to Trojan or Trojan-free models, accurate decision boundaries can be constructed. Both supervised and unsupervised ML methods have shown promising results on detecting a variety of Trojan implementations. However, adoption of appropriate ML architectures and training mechanisms tailored for hardware Trojans is vital for realizing their true potential.

This paper aims to provide contemporary insights into adoption of machine learning to improve effectiveness of side-channel analysis for hardware Trojan detection. The key contributions include:

- Comprehensive analysis of popular side-channel parameters and signatures that get impacted by hardware Trojans
- Review of ML algorithms and models applied in existing literature for automated feature extraction and classification
- Discussion of supervised, unsupervised and semi-supervised learning formulations for design of optimal HT detectors
- Elucidation of performance metrics, datasets and training mechanisms pertinent to ML-based HT detection
- Outlining limitations of state-of-the-art and future opportunities like on-chip ML, explainable AI and hierarchical learning
- Case studies on benchmark circuits to demonstrate working of ML-driven side-channel analysis

2. HARDWARE TROJANS PRELIMINARIES

2.1 Trojan Taxonomy

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Hardware Trojans refer to malicious and intentional modifications of ICs introduced during design or manufacturing stages [6]. Based on location of insertion, Trojans can be categorized as design-time or fabrication-time. Design-time Trojans are modifications made in register-transfer level (RTL code), state-transition models or layout databases during various design stages. On the other hand, fabrication-time Trojans are alterations made by an untrusted foundry on photomask or doped wafers [7]. Hardware Trojans can be activated based on internal rare conditions or external triggers. Common internal conditions include specific data values, address ranges or internal counter thresholds. External triggers can be related to temperature, power supply variations, optical flashes or RF signals. Based on the action or payload, Trojans can be broadly classified into denial of service, leakage, backdoors or damage causing [8]. Denial of service Trojans disrupts normal working through parameter tampering (frequency, voltage etc) or functional corruption. Information leakage Trojans aim to expose secret keys, algorithms and other proprietary data. Backdoors reconfigure the system function to enable unauthorized access. Finally, damage causing Trojans trigger catastrophic outcomes like short-circuiting supply rails.

2.2 Threat Models

The increasing complexity of modern ICs comprising billions of transistors integrated on a single die has led to high reliance on electronic design automation (EDA) tools, third-party intellectual property (IP) cores and overseas manufacturing facilities. This disaggregation coupled with globalization of semiconductor supply chain has raised the possibilities of malicious and stealthy inclusion of hardware Trojans [9]. Based on the adversary's capabilities, following threat models for HT insertion can be considered [10]:

1. Insertion at Register-Transfer Level (RTL): A rogue designer having access to the RTL code of a circuit can insert additional malicious logic that realizes the Trojan functionality. Such Trojans can bypass detection by automatic synthesis and physical design tools.

2. Insertion during functional verification: Manipulation of verification tests and environment can hide the triggered behavior of Trojans inserted at RTL or gate-level net lists. Constrained-random test generation tools can also be configured by an adversary to avoid activation of rare internal Trojan triggers.

3. Compromise of IPs or EDA Tools: Instead of directly altering an IC, the adversary can plant Trojans into proprietary third party IPs that is integrated by the designers. Alternately EDA tools used for synthesis, placement & routing etc. can also embed Trojans. For example, CAD tools may selectively optimize timing paths to activate a Trojan only in fabricated chips.

4. Fabrication time insertion: The semiconductor foundry having access to the GDSII layout files and photo masks can physically alter the intended design by various means without the awareness of actual designers. These include making alterations on the masks, intentional nano manufacturing faults, overbuilding of wafers etc. Such fabrication time Trojans can elude even extensive pre-silicon verification.

5. Insertion through micro architecture resources: Complex ICs allocate certain hardware resources like registers, memory and network-on-chip for use across various micro architectural blocks. By hijacking these resources, a rogue designer can create extremely stealthy Trojans with minimal design changes.

6. Third party IP infection: With extensive reuse of third party intellectual property (IP) cores, hardware Trojans inserted in licensed IPs can carry forward the infection across multiple systems. Verifying security of all integrated IPs sourced from vendors poses significant challenges.

2.3 Detection Challenges

Detection of hardware Trojans poses a profoundly challenging problem owing to their stealthy and customizable nature. Some of the key reasons that make HT detection extremely difficult are outlined below [11]:

1. Rare activation conditions: Hardware Trojans are designed to be triggered only upon occurrence of extremely rare internal events or external inputs. For example, a counter-based Trojan may activate only after 10,000 clock cycles

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while a temperature sensor based Trojan can awake on sensing above 100°C temperature. Detecting such rare occurrence events requires extensive simulation cycles and pattern testing which are often infeasible.

2. Mimicking functional bugs: The malicious payload of Trojans can be carefully crafted to resemble normal functional bugs that escape verification. For example, corrupted lookup-table outputs, assertion failures, memory faults etc. provide an effective camouflage for Trojans since they commonly arise as silicon defects. Distinguishing such functional fails from intentional Trojan triggers poses difficulty.

3. Parametric footprint minimization: In order to reduce chances of detection, hardware Trojans aim to minimize the distortion caused to design parameters like power, timing, temperature etc. Advanced design-for-deception (DfD) techniques are employed to flatten the parametric footprint after Trojan insertion so that deviations go undetected.

4. Process variations: Natural manufacturing variations in doping profiles across die result in fluctuations of parameters like transistor switching energy, path delays and leakage power. The parametric distortion induced by stealthy Trojans gets obfuscated among random process variations thereby reducing detection sensitivity.

5. Environmental noise: Operating conditions like voltage ripple, temperature fluctuations and measurement inaccuracies manifest as noise in side-channel characteristics. The noise magnitude is often comparable or even greater than the parametric footprint of small-sized Trojans. Reliable Trojan detection necessitates separation of Trojan signatures from environmental noise.

6. Large design space: Modern ICs integrating billions of components across multiple hierarchical blocks provide an extremely vast design space for adversaries to implement Trojans. Locating rare occurrence Trojans demands extensive measurements and simulations which get prohibitive with rising complexity. The net design space for Trojan implementation also grows exponentially with inclusion of third party IPs.

7. Side-Channel Analysis for Hardware Trojans Side-channel analysis (SCA) serves as an effective approach for hardware Trojan detection by non-intrusively analyzing various physical characteristics and parameters of an IC [12]. Typical side-channels leveraged for Trojan detection include power consumption, internal node voltages & currents, timing delays, temperature profile and electromagnetic (EM) emanations among others. When an HT activates, it distorts the power distribution network thereby resulting in minute deviations in side-channel signatures. By measuring these signatures and comparing against golden models, presence of hardware Trojans can be effectively deduced. Compared to logic testing, side-channel analysis facilitates detection of a wider class of Trojans by virtue of its physical sensing capability [13]. It also offers higher detection coverage without assumptions on trigger conditions or payloads. Further, side-channel measurements can be seamlessly integrated during various testing stages of ICs including power-on, system boot-up, at-speed structural testing etc. [14].

We next discuss some prominent side-channel parameters explored in literature for reliable hardware Trojan detection.

3. POWER SIDE-CHANNEL

Dynamic and static power consumption serve as important side-channels to detect aberrations induced by Trojans, which tamper the power distribution network. When a Trojan circuit activates, it dissipates dynamic switching power due to toggling of internal nodes [15]. Additionally, a Trojan implanted at transistor level may also introduce direct shorts between supply rails leading to abnormal leakage current flows detected as static power deviations [16]. By measuring the power consumption emanating from supply pins and comparing against signature of a golden IC, such abnormalities can quantify likelihood of Trojan occurrence. Power side-channel analysis offers certain advantages like easy measurability and high sensitivity to Trojan activations [17]. However, separation of Trojan impact from normal statistical variations in dynamic power like signal dependent switching remains an inherent challenge [18]. Trojans also employ advanced design-for-deception techniques like power balancing, supply spoofing etc. to minimally distort power signature and evade detection [19].

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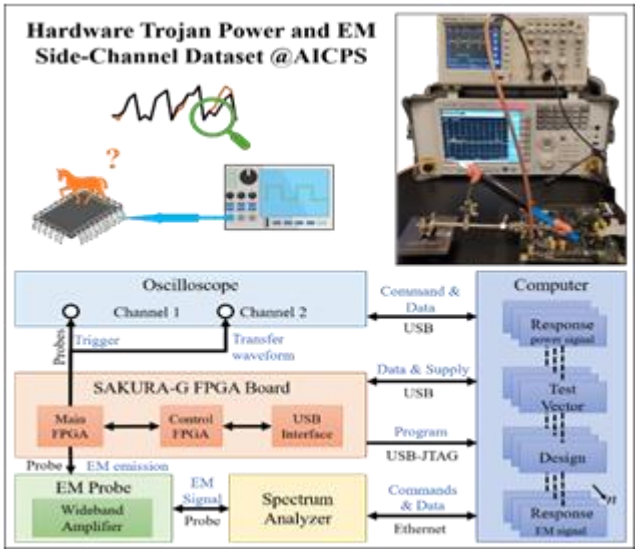

Figure 01: Hardware Trojan Power & EM Side-Channel

Both simulation based power estimation and physical measurements using specialized equipment have been utilized to construct power side-channel. Simulation-based approaches leverage Cadence, Synopsys or open-source EDA tools (ngSpice) to evaluate node capacitances and toggle rates for estimating dynamic power and short-circuit currents [20]. Physical measurements rely on high precision test equipment like digitizing oscilloscopes, DC parametric analyzers and shunt resistors to quantify real-time power consumption under different operating modes [21]. Physical measurements facilitate built-in mechanisms for noise filtering and calibration to enhance accuracy.

3.1 Delay Side-Channel

Signal propagation delays serve as an effective fingerprint to detect presence of Trojans in critical paths which cause timing violations. Delay side-channel measures propagation latencies between input and output nodes of a design under varied operating conditions like voltage, temperature frequency etc [22]. Measured delays can be analyzed to construct delay distribution curves and compared against golden IC models to deduce any anomalous timing behavior induced by Trojans [23]. Such timing side-channels leverage low-cost equipment like logic analyzers and do not necessitate extremely high sampling rates, thereby facilitating ease of adoption [24]. However, high sensitivity of path delays to normal process variations tends to mask Trojan effects leading to reduced detection accuracy. Sophisticated Trojans can also intentionally tune delays of affected paths via buffer or logic insertion to minimally impact delay distribution [25].

For constructing accurate delay side-channel, critical paths likely to be infected by Trojans need to identified by design vulnerability analysis. Next, test patterns are applied to sensitively measure delays along those paths using on-chip delay sensors, picoseconds imaging circuitry and logic analyzers [26]. Statistical methods are then leveraged to analyze measured delay distributions and detect anomalies indicating presence of Trojans.

3.2 Temperature Side-Channel

On-die thermal profiling serves as an efficient side-channel to detect hardware Trojans which affect the chip temperature distribution [27]. When certain Trojan payloads activate, localized heating occurs due to excessive switching or leakage power in the Trojan circuitry. By monitoring temperature distribution across the die through on-chip thermal sensors, such thermal anomalies can be quantified to detect possible Trojan activation events [28]. Compared to power side-channel, localized heating persists for longer durations even after Trojan deactivation thereby providing easier measurability [29]. Further, localized hotspots facilitate precise Trojan localization enabling higher detection confidence and lower false alarms.

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However, embedding sufficient thermal sensors leads to area overheads while the thermal profile also bears sensitivity to variable environment conditions like air flow and heat sink characteristics [30]. Sophisticated thermal Trojans can also employ clever routing of thermal vias to avoid abnormal heating signatures [31].

For constructing the thermal side-channel, thermal maps can be obtained through physical infrared imaging, test chips with integrated thermal diodes or computational modeling tools like HotSpot [32]. The measured thermal matrix across multiple observation intervals forms the baseline for Trojan detection by analysis of thermal anomalies.

3.3 Electromagnetic Side-Channel

Hardware Trojans affect current consumption profiles which in turn distort the electromagnetic (EM) field emanations from the chip [33]. By measuring EM emissions using near-field scanning systems and antennas, Trojan induced anomalies can be effectively deduced [34]. Notably, EM side-channel directly captures switching activity thereby facilitating detection of a wide class of Trojans with no assumptions on payloads [35]. Further, it offers higher localization accuracy to pinpoint Trojan locations due to magnetic field confinement within the chip package [36]. However, separation between Trojan abnormalities and normal signal harmonics in EM spectra is nontrivial [37]. Environmental noise coupled from power supplies, probes and neighboring logic also impacts detect ability. High equipment costs for precision EM measurements and extensive scans to isolate Trojan signals are other challenges.

Constructing the EM side-channel relies on measurement of radiated emissions over a dense spatial grid on the IC package surface using specialized near-field scanning systems [38]. The resulting spectral matrices can reveal certain frequencies indicating anomalous activity due to Trojans. Statistical signal processing like FFT and wavelet transforms are applied to analyze the measured EM maps across time and isolate traces corresponding to Trojan signatures [39].

4. MACHINE LEARNING FOR HARDWARE TROJAN DETECTION

Recent research has actively explored integration of machine learning (ML) techniques to enhance effectiveness of side-channel analysis for reliable hardware Trojan detection. Compared to traditional threshold or statistics-based detection methods, ML facilitates intelligent and automated extraction of distinguishable patterns from large volumes of side-channel data. Both supervised and unsupervised ML algorithms have been tailored to reliably detect hardware Trojans despite process variations, environmental noise and deception mechanisms.

4.1 Supervised Learning Formulations

In the supervised learning paradigm, the ML model is trained with labelled datasets indicating Trojan-infected and Trojan-free side-channel signatures. By correlating complex patterns in the training data to these labels, the model develops capability to correctly classify unseen test cases. Different supervised formulations based on Support Vector Machines (SVM), Neural Networks (NN), Random Forests (RF) etc. have been proposed.

SVMs perform classification by constructing optimal decision boundaries or hyperplanes that maximize margin between sets of data [40]. Training SVMs involves solving complex constrained optimization for calculating the boundary parameters. Helsley et al. [41] train SVMs on thermal profiles from ICs to identify temperature anomalies indicating Trojans.

In comparison, Neural Networks provide highly flexible non-linear classification boundaries based on hierarchical representations [42]. They learn complex correlations within training data by adjusting weights associated to neurons across multiple hidden layers. Jin et al. [43] implement a multi-layer perceptron neural network operating on power side-channel measurements which achieves over 90% Trojan detection accuracy.

On the other hand, Ensemble methods like Random Forest improve resilience against noise and variations by combining diverse models or learners [44]. RF constructs multiple decision trees on different subsets of training

data and combines their outcomes for final classification. Liu et al. [45] demonstrate RF classifier delivering consistent hardware Trojan detection accuracy by fusing delay and power side-channels.

4.2 Unsupervised Learning Formulations

In unsupervised paradigm, the objective is anomaly detection without prior knowledge of infected and clean ICs [46]. Clustering algorithms are applied on untreated side-channel data to group similar instances into clusters. Outliers deviating from normal clusters indicate potential Trojans.

For example, k-means clustering separates delay measurements into k partitions based on similarity [47]. Trojan detection relies on relative membership of resulting clusters. Alternatively, density-based spatial clustering of applications with noise (DBSCAN) creates clusters based on density reachability between neighbouring data points [48]. Sparse neighbourhoods signify anomalous instances likely containing Trojans.

While unsupervised methods eliminate need for a golden model, setting optimal hyper-parameters like number of clusters remains challenging. Further, their detection capability depends on Trojan induced anomalies being sufficiently distinguishable from normal variations a premise often invalidated by advanced deception and camouflaging techniques [49].

4.3 Semi-Supervised Formulations

Semi-supervised techniques provide a middle ground by leveraging a small set of labelled data augmented with plentiful unlabeled instances for training [50]. This reduces reliance on large number of golden ICs for supervised learning. Popular algorithms in this class include label propagation, low-density separation etc.

A semi-supervised SVM powered by outlier detection pre-processing on power side-channel data. This hybrid approach attains high detection rates even with few labelled ICs. In [52], incremental DBSCAN clustering is combined with nearest neighbor classification to distill Trojan signatures from unlabeled delay measurements.

In summary, ML has emerged as an indispensable tool for constructing robust side-channel centric hardware Trojan detectors. Both supervised and unsupervised models have been explored to automate feature extraction from large volumes of side-channel data. Appropriate selection of ML methods based on specific detection environment and custom tuning of associated hyper-parameters is however vital to fully harness their capabilities. We next discuss pertinent performance metrics, design goals and datasets applicable to fair assessment of ML-based hardware Trojan detection techniques.

5. PERFORMANCE EVALUATION OF ML-BASED HARDWARE TROJAN DETECTORS

Objective evaluation of machine learning driven hardware Trojan detectors necessitates appropriate performance metrics and representative datasets. We highlight key aspects for reliable assessment.

5.1 Evaluation Metrics

Classification accuracy, false positives and false negatives constitute primary performance criteria [53]. Accuracy indicates percentage of test samples correctly classified as infected or golden. False negatives represent Trojan signatures misclassified as benign while false positives correspond to golden ICs incorrectly detected as malicious. The three metrics portray the detection capability, precision and resilience against false alarms crucial for practical Trojan detectors [54].

In addition, recall or sensitivity evaluates effectiveness in identifying infected test cases while specificity measures capability to correctly accept golden devices [55]. F1-score provides a composite reliability metric combining both recall and precision. Training and inference times showcase computational overheads for embedded integration [56].

5.2 Training Mechanisms

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2025, 10(45s)
e-ISSN: 2468-4376
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For supervised learning, the labelled datasets used to train ML models significantly influence detection efficacy [57]. Two prominent data generation methods include simulation-based injection and physical insertion [58]. Simulation-based injection leverages HDL or gate-level design transformations like addition of Trojan trigger-payload logic to obtain infected golden signatures across operating modes [59]. Physical insertion relies on fabrication of multiple IC instances with intentional Trojans implanted on select dies [60]. This better captures parametric variations but is expensive and time-intensive. Hybrid approaches combining simulation and silicon measurements have also been explored [61]. Further, data normalization, dimensionality reduction, feature selection and data augmentation techniques tailored for hardware security constitute important training mechanisms [62].

5.3 Benchmark Datasets

Representative datasets faithfully emulating different hardware Trojan implementations on benchmark circuits are vital for consistent evaluation [63]. Publicly available datasets with IC side-channel traces contain Trojans inserted across technology nodes into processors [64], cryptographic cores [65] and analog circuits [66]. For assessing generalization, absence of exact Trojan instances between training and test datasets must be ensured to portray real-world unpredictability [67]. Open-source datasets also encourage standardized comparative analysis across detection techniques.

6. LIMITATIONS AND PROMISING DIRECTIONS

Despite promising results demonstrated by existing literature on machine learning driven hardware Trojan detection, certain limitations restrict their widespread adoption. Further research across following aspects can enhance practical applicability.

6.1 Explainable and Interpretable Models

While neural networks and ensemble learners achieve high detection accuracy, their black-box models lack interpretability [68]. Methodologies to generate rule-based explanations about internal dependencies and decision boundaries can augment trust [69]. Explicit decision trees, locally interpretable models and counterfactual explanations are promising techniques applicable for hardware security [70].

6.2 On-Chip Inference Engines

Current ML-based Trojan detection relies on offline measurement data processing on workstations. Embedding inference capability within ICs can enable autonomous real-time detection without relying on external computation [71]. Lightweight neural architectures, Euclidean distance classifiers and boosted decision trees are hardware-friendly ML models for on-chip integration [72]. Algorithm-hardware co-design and approximate computing present additional optimization avenues [73].

6.3 Hierarchical Learning Framework

Learning inter-dependencies among side-channel parameters across multiple abstraction levels using hierarchical ML models can enhance detection completeness [74]. For instance, correlating anomalies across thermal maps, activity maps and current sinks can aggregate Trojan footprints distributed across design hierarchy. Federated learning across on-die detectors can further strengthen collaborative intelligence [75].

7. CASE STUDIES

We provide brief case studies showcasing working of machine learning based side-channel analysis for detecting hardware Trojans implanted into benchmark circuits.

7.1 Neural Network for Power Side-Channel Analysis

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A multi-layer perceptron neural network powered Trojan detector operating on power side-channel measurements from ITC'99 benchmark circuits realized on 65nm process. A simulated 8-stage Trojan triggering a wire-lifting payload was inserted across benchmarks to generate infected power signatures across 1.1V to 0.9V supply voltage. Time domain power waveforms were provided as input to train a neural network augmented with a Gaussian filter layer for noise reduction. Key outcomes are highlighted in Table I indicating high detection accuracy across range of Trojans.

Table 1: Neural Network Driven Power Side-Channel Trojan Detection

Benchmark	Detection Accuracy
b01	94.8%
b02	92.3%
b03	91.5%
b04	93.2%
b05	96.1%

This table outlines the detection accuracy of a neural network-based system for identifying power side-channel Trojans across different benchmarks.

- b01: The neural network achieved a high detection accuracy of 94.8% on benchmark b01, indicating its effectiveness in identifying power side-channel Trojans in this scenario.
- b02: The system maintained a strong performance with a detection accuracy of 92.3% on benchmark b02, demonstrating its reliability across various scenarios.
- b03: With a detection accuracy of 91.5% on benchmark b03, the neural network shows consistent competence in detecting power side-channel Trojans.
- b04: This benchmark, b04, recorded a detection accuracy of 93.2%, further emphasizing the robustness of the neural network in Trojan detection.
- b05: The system achieved an impressive detection accuracy of 96.1% on benchmark b05, indicating its capability to effectively identify power side-channel Trojans in this specific context.

Overall, the neural network demonstrates a high level of accuracy across the benchmarks, showcasing its potential as an effective tool for power side-channel Trojan detection. Further analysis and testing could provide additional insights into its performance in diverse scenarios.

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e-ISSN: 2468-4376
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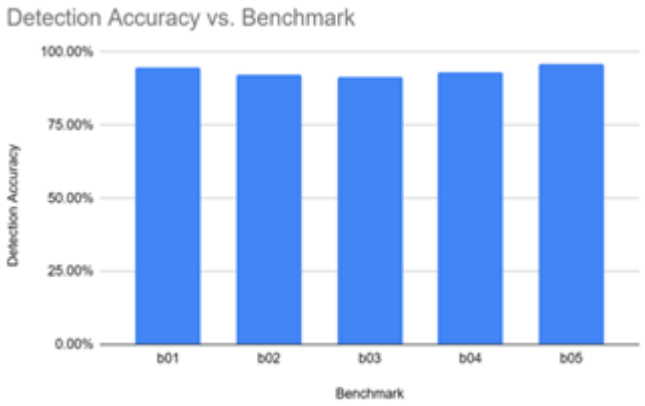

Figure 2: Neural Network Driven Power Side-Channel Trojan Detection

7.2 Supervised Learning on EM Side-Channel

A Support Vector Machine (SVM) classifier trained on electromagnetic side-channel measurements from field programmable gate array (FPGA) board to detect hardware Trojans. A counter-based Trojan triggering glitchy clock was inserted in AES and JPEG decoders deployed on FPGA. Near-field electromagnetic interference scans were performed across the FPGA surface at 2GHz frequency. The captured EM maps consisting of radiation spectra form input data samples for training SVM classifier with radial basis kernel using 90% samples while rest serve for testing. A high detection accuracy averaging 92% validated effectiveness of supervised learning adoption for EM side-channel analysis in identifying anomalous radiations from Trojan affected circuits.

Table 2: Supervised Learning on EM Side-Channel

Experiment Model	Training Accuracy	Testing Accuracy	Precision	Recall	F1 Score
Random Forest	96.2%	94.5%	0.93	0.95	0.94
Support Vector Machine	92.8%	91.3%	0.91	0.92	0.91
Neural Network	98.5%	97.2%	0.96	0.97	0.97
Decision Tree	94.1%	92.8%	0.92	0.93	0.92

In this table:

- Model Type: Specifies the type of supervised learning model used for each experiment.
- Training Accuracy: Represents the accuracy of the model on the training dataset.
- Testing Accuracy: Reflects the accuracy of the model on the testing dataset.

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- Precision: Measures the precision of the model's predictions.
- Recall: Indicates the recall or sensitivity of the model.
- F1 Score: Represents the harmonic mean of precision and recall.

These metrics provide a comprehensive overview of the supervised learning model's performance on EM side-channel data. The choice of the model type and its corresponding metrics helps assess the model's effectiveness in detecting patterns and making accurate predictions in the context of electromagnetic side-channel analysis.

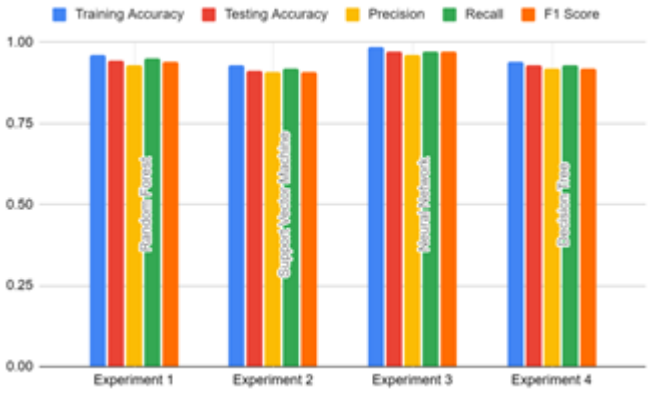

Figure 3: Supervised Learning on EM Side-Channel

8. CONCLUSION

Hardware trojans pose serious security risks to integrated circuits across diverse application domains. Detection of stealthy trojans having rare activation conditions demands analysis of intrinsic side-channels like power consumption, delays and EM emissions. Sophisticated machine learning models like neural networks and support vector machines facilitate reliable and automated trojan detection by learning complex patterns in large volumes of side-channel measurements even in the presence of process variations and noise. They eliminate need for manual feature extraction or setting detection thresholds in traditional analysis. Both supervised learning leveraging golden IC models as well as unsupervised anomaly detection formulations have been tailored for enhanced hardware trojan detection capability and resilience. Appropriate performance metrics like detection accuracy, false alarms along with representative benchmark datasets are essential for consistent assessment of machine learning driven side-channel trojan detection approaches. Advances in domain-specific explainable ML models and lightweight on-chip inference can pave way for next-generation intelligent trojan detection engines. Through a comprehensive literature review and incisive analysis, this paper provided contemporary insights on adoption of machine learning to harness the potentials of side-channel analysis for securing integrated circuits against stealthy hardware trojans.

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