

# The Neural Cryptanalyst

by Ahmed Taeha

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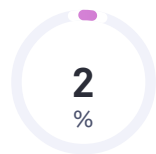


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# The Neural Cryptanalyst

Taha 1

The Neural Cryptanalyst: Machine Learning-Powered Side Channel Attacks – A Comprehensive Survey

This manuscript began as a term project for Johns Hopkins University for course EN.695.641.81.SP25 – Cryptology (Instructor: Prof. Tom McGuire, Spring 2025). It has since been expanded into a public survey for the benefit of the side-channel-analysis research community.

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Abstract

Machine learning transforms side-channel attacks. Where once one needed an extensive background in cryptography to exploit vulnerabilities, the new level of expertise—and number of traces needed—significantly lowers for key recovery. We evaluate convolutional neural networks (CNNs), Long Short Term Memory (LSTM), and Transformers on power traces from side-channel attacks on AES, RSA and ECC. Deep learning only needs 80%-90% less traces than differential power analysis. CNNs can attack first-order masked AES with only 500-1000 traces (versus 5000-10000) with an accuracy of 70-85%. Second-order masked attempts fall victim to ensemble attacks needing only 3000-5000 traces. Transformers exceed 20-40% better than CNNs while LSTMs level off at

60-75% even though it's off by 1000 samples. The vulnerabilities we discover include constant-time implementations which leak information due to power variations; Montgomery ladder RSA leaks 60-70% of its exponent bits and even Curve25519 succumbs to transformer attacks. Mixed masking, shuffling, and hiding implementations do not hold up either. Our open-source implementations show that neural networks can find non-linear mapping patterns and automatically extract features without the need for cryptographic background. Our findings show that current defenses do not protect against machine learning based attacks. The capability to automate and widen the net of attack is a clear threat to all embedded cryptographic systems worldwide. Keywords: Side channel analysis, Machine learning, Power analysis, Neural networks, Cryptographic implementations, AES, RSA, ECC

## Introduction

Side channel attacks are a sophisticated type of cryptanalysis that target not the calculated, formulaic understanding of an algorithm but information gleaned unintentionally through physical channels while the cryptographic algorithm is running. These physical channels include power consumption, electromagnetic emanations, acoustic emissions, or execution time. Side channel analysis (SCA) can be traced back to Kocher's 1996 timing attacks paper [12] and his subsequent 1999 differential power analysis work [11], and the growth of SCA since the late 1990s combined with the integration of

machine learning (ML) and deep learning (DL) environments has created what we now term AI-enhanced side channel attacks.<sup>18</sup>

Where before extensive attacker involvement was required to the extent that statistical tests needed to be run to potentially determine a successful attack,<sup>22</sup> now learning the parameters to identify a successful attack is no longer required knowledge and attack success rates have improved significantly [2].<sup>19</sup> Picek et al. (2023) synthesizes findings from previously published works to document this transformation that deep learning has enabled for physical side channel analysis, allowing researchers to pursue more streamlined yet highly successful attacks.<sup>20</sup> For example, where DPA and CPA required the attacker to know what the algorithm was doing,<sup>21</sup> how the hardware or software operated, AI attacks require basic background knowledge [3] of the target algorithm and collection of power traces from the device to potentially extract secret keys.<sup>23,24</sup><sup>24</sup><sup>23,24</sup><sup>26</sup>

This survey examines the advancements, methods of attack and results of AI-based side channel attacks focusing on power analysis attacks against crypto-processing hardware and software.<sup>28</sup> The reader will learn the architecture of the neural nets used to attack,<sup>29</sup> the coding for execution, the vulnerabilities exposed by trained attacks on predominant crypto standards, and the effectiveness of defenses against such novel attacks.

## Section 2

### 2.1 Technical Foundations of Power Analysis Attacks

The concept of power analysis attacks stems from the idea that the power a device expends to calculate information represents the information itself.<sup>30</sup> Therefore, if one can physically determine how much power a device exerts while calculating, it may be possible to extract sensitive information. This theory is valid because integrated circuits expend different power amounts<sup>33</sup><sup>33</sup>

under different operating conditions and with different data values.<sup>31,33</sup> For instance, complementary metal-oxide-semiconductor (CMOS) integrated circuits—which make up almost every computing device produced and utilized today—expend power one way during a charge (changing configurations)<sup>34</sup> and another when static (off). Further, CMOS integrated circuits expend power to switch states when determining binary 1s and 0s as input data [11].<sup>35</sup>

The standard power calculation equation for CMOS is [11, 19]:

$$P = \alpha \times C \times V^2 \times f$$

Where: P = Average Power Consumption  $\alpha$  = Activity Factor C = Load Capacitance V = Voltage f = Frequency

Where  $\alpha$  typically ranges from 0.01 to 1.0 depending on circuit switching activity

The total equation for power consumption is the sum of three factors [19]:

$$P_{\text{total}} = P_{\text{dynamic}} + P_{\text{static}} + P_{\text{short-circuit}}$$

Where  $P_{\text{dynamic}} = \alpha \times C \times V^2 \times f$  is the power consumed due to switching when logic changes occur,  $P_{\text{static}} = I_{\text{leak}} \times V$  is the power consumed by leakage current which occurs when transistors do not switch properly,<sup>36</sup> and  $P_{\text{short-circuit}} = I_{\text{sc}} \times V \times f$  is the power consumed by the momentary short-circuit current that exists when PMOS and NMOS are turned on simultaneously for a very short time during switching.

The physics of CMOS switching creates an exploitable correlation between processed data and power consumption. For instance, in a CMOS design, a logic gate consists of complementary pairs of p-type and n-type MOSFETs. When logic toggles, current passes through the gates to charge or discharge the output capacitance. Thus, the total power used is directly proportional to how many gates toggled,<sup>38</sup> and the logic is informed directly by what data is processed.<sup>39</sup> Thus, if more logic toggles, power consumption follows suit. In

addition,<sup>40</sup> static CMOS power consumption is negligible when high or low states are active; at the same time,<sup>40</sup> there is an incremental power increase when switching states.

Thus, when involving encryption,<sup>41</sup> the power consumption activity factor  $\alpha$  becomes data dependent,<sup>41</sup> which attackers can then use to their advantage.

This is called a side channel vulnerability,<sup>42</sup> which occurs based on leakage modeling expectations.<sup>43</sup> The two most significant leakage models are Hamming Weight (HW) and Hamming Distance (HD),<sup>44,45</sup> although what occurs in the real world may differ from what is purely expected.<sup>46,47</sup>

The Hamming Weight model indicates that power is drawn based on how many bits in the value are equal to one.<sup>48</sup>

$$HW(x) = \sum_{i=0}^{n-1} x_i$$

This models reality somewhat because it's true that manipulating a value with more 1 bits is going to probably require more signal toggling in the combinational logic needed to generate it,<sup>50</sup> but it's a theory based on observation.<sup>51,52</sup>

The Hamming Distance model indicates that power consumed is based on how many bit transitions occur.<sup>53</sup>

$$HD(x, y) = HW(x \oplus y)$$

This models reality a little better because it applies directly to how many transitions are made when using dynamic power and the sequential logic required to switch registers from value x to value y.<sup>54</sup>

Therefore, these are all models of leakage that are analogous to what one might find in the real world; however, they do not account for all leakage. For example, with integrated circuits, there could be leakage based on some bits more than others (certain bit positions leak worse than others) or value-dependent leakage (certain data values give a different signature of power).<sup>55,56</sup> Either way, the



best method to determine which type of leakage model applies to one's situation is through real testing on the actual targeted device [4].

# Minimal implementation of power consumption models

```
def hamming_weight(value):
```

```
    return bin(value).count('1')
```

```
def hamming_distance(value1, value2):
```

```
    return hamming_weight(value1 ^ value2)
```

# Complete implementation available at

[github.com/ahmedtaha100/ML\\_Cryptanalyst](https://github.com/ahmedtaha100/ML_Cryptanalyst)

In addition to hardware side channel attacks with considered leakage, much is at stake for assessment of side channel attacks as well. The Nyquist-Shannon theorem states that sampling must occur at greater than double the highest frequency of interest [13]. A 100 MHz device has certain power consumption that operates with harmonics into the GHz range, meaning that to accurately obtain all power characteristics, one needs sampling frequencies greater than 5 GS/s [14]. Yet many side channel attacks find success with much lower sampling frequencies, such as 1 GS/s [2].

The quality of measurements follows the Signal-to-Noise Ratio (SNR):

$$\text{SNR} = \text{Var}(S_{\text{signal}}) / \text{Var}(S_{\text{noise}})$$

where  $\text{Var}(S_{\text{signal}})$  is the variance of the signal dependent measurement and  $\text{Var}(S_{\text{noise}})$  is all sources of noise from thermal noise to quantization noise to environmental interference to algorithmic noise from simultaneous operations on the device. The SNR across measurements in dB is as follows:

$$\text{SNR}_{\text{dB}} = 10 \times \log_{10}(\text{SNR})$$

In a controlled environment with access to sophisticated oscilloscopes, shielding, and stable triggering, one is able to obtain SNR values greater than 20 dB for the unprotected measurements [15]. For the protected measurements where countermeasures take place, the SNR may be negative for the leakage of interest, which means more extensive statistical testing is required. For attacks in the field or on devices where countermeasures are applied, the SNR may be measured below 0 dB, which means extensive signal processing and many more traces are needed for successful key recovery [15]. Traces also need to be triggered at the proper time to ensure time-domain alignment. When traces are out of alignment, effective SNR drops, and attacks fail. IO patterns, EM emissions for specific operations, or trigger circuits that exist only in the lab provide triggering [14].

Despite power traces being one of the easiest and most common traces, EM traces can be even more effective. EM emissions are easier to localize than power emissions—they can be restricted to certain areas of a chip and avoid some detection and prevention measures that power might be vulnerable to [16]. The same leakage models and leakage analysis that exist for power traces also apply to EM [14].

Whereas one needs traces, one also needs to understand the points of interest (POI) within the traces. That is, which samples/times demonstrate leakage? For example, when an implementation has no protection, the POI will coincide with when vulnerable intermediate values are read/written. Thus, many researchers have automated POI detection from statistical means (e.g., t-test) or mutual information [2].

These physical characteristics are leveraged by a number of classical power analysis techniques. For instance, Simple Power Analysis (SPA) has an attacker simply looking at power traces and determining what has happened based on

what he or she sees along the way.<sup>80,81</sup> For instance, the square-and-multiply RSA algorithm generates unique traces for where squaring occurs and where multiplication occurs to the extent that one can determine what bits are associated with the secret exponent [17]. SPA requires intimate knowledge of the implementation, but it only needs a single trace.

Differential Power Analysis (DPA) is somewhat similar because it too relies<sup>82</sup> upon power consumption and vulnerabilities generated from such analysis;<sup>83</sup> however, this time, the attacker must correlate consumption with the likeliest values generated from set keys. The attacker takes a key guess and computes what intermediate values would yield during execution—computes power consumption—and repeats for each successive key guess, enabling them to determine which hypothesis has the highest correlation with consumed power.<sup>84</sup> DPA does not require implementation awareness but instead of a single trace,<sup>85</sup> it needs thousands [11].<sup>86</sup>

Correlation Power Analysis (CPA) is essentially DPA but with the Pearson correlation coefficient.<sup>87</sup> It measures how well the predicted power and measured power correlate with each other.<sup>88</sup> CPA does this in a transparent fashion by using a leakage model like HW or HD to predict the amount of power used.<sup>89</sup> So, if a leakage model holds true for the device under attack, then CPA is better than DPA [6].<sup>90,91,92</sup>

The best type of power analysis attack relative to information-theoretic gain is called the Template Attack [18].<sup>93</sup> This requires the attacker to profile an identical device which allows for multivariate Gaussian templates—meaning every possible intermediate value has its own power consumption distribution.<sup>94</sup> The attack phase then applies maximum likelihood estimation to correlate the observed traces to the appropriate template.<sup>95</sup> This attack can use pooled covariance matrices across the templates so as to lessen the profiler's need for

access.<sup>97</sup> This is the most optimal power attack; it works from minimal traces but requires extensive profiling access.

These traditional attacks operate under the assumption that there is no tamper protection.<sup>98</sup> However, contemporary cryptographic devices employ countermeasures including masking (splitting critical variables into random shares), shuffling (randomization of operation order), and hiding (noise or dummy operations)<sup>99</sup> that make these attacks significantly more difficult.<sup>100</sup> For instance, these countermeasures<sup>73</sup> can cause SNRs to become negative and demand higher-order assessment or more complicated approaches,<sup>101</sup> which are the basis for the machine learning techniques assessed in later sections.<sup>10</sup>

## 2.2 Threat Model and Assumptions

This subsection describes the threat model for the side channel attacks<sup>103</sup> studied in this research, what the attacker can (and cannot) do<sup>102</sup> and under what attack parameters.<sup>11</sup>

### Attacker Capabilities

The attacker has physical access—power measurements occur centimeters away, EM (electromagnetic) measurements millimeters away from the chip—and thus, effective operation is only from nearby.<sup>104</sup> There is no virtual/remote operation.<sup>105</sup> The attacker does NOT destroy the device or intentionally interfere with it. This attack is non-invasive. A semi-invasive attack—where a chip is decapsulated although no interference occurs with the circuitry now visible when the chip is opened<sup>106</sup>—is associated with other research.<sup>107</sup>

The attacker has the following at their disposal: a digital oscilloscope with a sampling rate of at least 100 MS/s and the common 8-12 bit resolution utilized in side channel attacks;<sup>108</sup> current probes or resistive shunts for IC power measurements;<sup>109</sup> differential probes for achieving a good enough signal-to-noise<sup>110</sup>

ratio; near-field EM probes for H-field and E-field characterizations; stable triggering.

The attacker has access to deep learning training. The models evaluated in our work, for instance, operate on GPUs with at least 8GB memory and require hours or days to train depending on the architecture complexity and the size of the training and testing dataset.<sup>111</sup>

# From

[github.com/ahmedtaha100/neural\\_cryptanalyst/src/neural\\_cryptanalyst/benchmarks/benchmark.py](https://github.com/ahmedtaha100/neural_cryptanalyst/src/neural_cryptanalyst/benchmarks/benchmark.py)

if GPU\_AVAILABLE:

gpus = GPUUtil.getGPUs()

<sup>112</sup> if gpus:<sup>113</sup>

gpu\_memory = gpus[0].memoryUsed<sup>114</sup>

The attacker knows the encryption scheme the side channel attack is targeting—AES, RSA, or ECC—but does not know the secret keys or random masks. The attacker knows the operating environment, whether hardware/software based,<sup>11</sup> and the estimated clock frequency. For profiled attacks, the attacker possesses the targeted device or a similar one and has control over the input during profiling<sup>117 117</sup>.

The fact that data collection allows for profiling means the attacker has access to a wealth of traces from the victim device. The profiling step occurs on a scale<sup>118</sup> of hundreds of thousands or millions of traces with the key known. This does<sup>119</sup> not mean, however, that this is the case during the attack step; typically<sup>120</sup> unprotected implementations require 50-200 traces, first-order protected implementations require 500-5,000 traces, and second-order (or more) protected implementations could require in excess of 50,000 traces.<sup>121</sup>

Attacker Limitations

There are several important limitations that restrict the attacker's capabilities. The attacker cannot have invasive access, meaning no internal circuit manipulation, no fault injection, nor operational changes to the device. The attacker cannot inject malware via software or firmware changes to the victim device. In some cases, the attack collection window is limited (for instance, a payment card attack can happen in seconds while the card is engaged). The attacker has no access to key storage/key generation aside from side channel leakage.

### Environmental Assumptions

The attack environment consists of noise sources and operational conditions. Noise sources include thermal noise at 290K (measurement devices usually output -174 dBm/Hz taking into consideration room temperature), quantization noise (for example, SNR is approximately  $6.02N + 1.76$  dB for N-bit ADC which is the theoretical maximum for analog-to-digital conversion), electromagnetic noise from the surrounding area, and algorithmic noise (i.e., the attacker works simultaneously with work being done on the attacked device).

# From

`github.com/ahmedtaha100/neural_cryptanalyst/src/neural_cryptanalyst/models/power_model.py`

```
def generate_thermal_noise(self, num_samples: int, bandwidth: float) ->
```

```
np.ndarray:
```

```
noise_power = 4 * self.k_boltzmann * self.temperature * bandwidth
```

```
noise_voltage = np.sqrt(noise_power)
```

```
return np.random.normal(0, noise_voltage, num_samples)
```

Operational conditions are that the attacked device works under nominal conditions—voltage standard  $\pm 10\%$  and temperature 0-70 degrees C. There is a

reliable clock source; jitter occurs under 1% of the clock period, and operation is repeatable so that the same operation produces statistically similar traces. The following are the measurement conditions: Sampling rate is at least 5× the anticipated clock frequency for power analysis. Measurement bandwidth is DC to at least 2× clock frequency for capturing relevant leakages. Triggering is stable with jitter below 10% of anticipated operating time. Signal-to-noise ratio is 20 dB (without protection) and -10 dB (with protection; masking countermeasures should be applied).

### Attack Scenarios

The attack scenario is drawn from the following real-life situations. Pre-certification testing occurs because device manufacturers generate test vectors during development to identify vulnerabilities pre-certification arrival. Laboratory assessment is where security assessors have access to everything and collections are unlimited for profiling and attacking stages. Finally, certification assessment occurs when a third-party assessment laboratory assesses the device against Common Criteria or FIPS 140-3 requirements either as a standardized test vector.

So why do these three models motivate? Field attacks represent the final deployment, meaning attackers only have limited access for a limited amount of time in a noncontrolled environment having not much more profiling than what's provided during final deployment. Supply chain attacks mean that attackers have access but only for as long as packaging or shipping, which means they are more likely to profile their attack sample based on the samples received during production. Remote power analysis means that attackers can perform attacks based on unintentional electromagnetic emanation that is perceivable at a distance or based on power consumption activities observable in shared power supply systems.

## Survey of attacks and exclusions

This survey studies passive side channel attacks relative to power consumption and does not include active fault injection attacks (voltage/clock glitching and laser fault injection), invasive attempts (probing, reverse engineering), software vulnerability/protocol level exploits, acoustic/optical or other exotic side channels, and composite attacks requiring multiple side channel activation simultaneously.

This threat model holds for the machine learning techniques proposed here. Other evaluations would be necessary for more robust attackers with invasive access or more minimal attackers operating remotely.

### 2.3 The Machine Learning Elements of Side Channel Attacks

Machine learning transforms side channel attacks from complex exploits requiring unique expertise to automated attack processes. Machine learning transforms side channel attacks through two main approaches: profiled attacks using identical devices for training, and non-profiled attacks that learn directly from the target.

The first is a profiled attack, meaning that the attacker has the same or a similar device to train on. The profiling phase entails gathering power traces from the profiling device while it engages in cryptographic activity with known keys; this process creates labeled datasets that allow machine learning models to understand the classification of power patterns to specific key values or intermediate functions. The attack phase utilizes the trained model on the attack power traces from the attack device with unknown keys. This involves supervised learning and requires only a few attack power traces to achieve high success rates.

# From

[github.com/ahmedtaha100/neural\\_cryptanalyst/src/neural\\_cryptanalyst/attacks](https://github.com/ahmedtaha100/neural_cryptanalyst/src/neural_cryptanalyst/attacks)



ks/profiled.py

class ProfiledAttack:

```
def train_model(self, traces: np.ndarray, labels: np.ndarray,
validation_split: float = 0.2):
```

```
    """Train the underlying neural network model."""
```

```
    X, y = self.prepare_data(traces, labels, num_features=num_features,
augment=True)
```

```
    y_onehot = tf.keras.utils.to_categorical(y, num_classes=256)
```

Non-profiled attacks bring the assault directly to the victim device, implying that it attacks a device without ever being trained on the same device

beforehand. This means that the ML model must acquire information from the non-labeled traces and likely rely on unsupervised or semi-supervised learning techniques to determine feature correlation with expected hidden information.

This obviously creates a much more complicated scenario, albeit a much more realistic one, should a malicious entity not be able to create a profiling device.

# From

[github.com/ahmedtaha100/neural\\_cryptanalyst/src/neural\\_cryptanalyst/attacks/nonprofiled.py](https://github.com/ahmedtaha100/neural_cryptanalyst/src/neural_cryptanalyst/attacks/nonprofiled.py)

```
def template_matching_attack(self, traces: np.ndarray, plaintexts: np.ndarray,
n_clusters: int = 9) -> np.ndarray:
```

```
    kmeans = KMeans(n_clusters=n_clusters, random_state=42)
```

```
    clusters = kmeans.fit_predict(features)
```

Ultimately, the attack's machine learning oriented approach has the same logic to create a linear pipeline. For example, for data collection, power traces are recorded via oscilloscopes or dedicated side channel acquisition devices where data collection occurs from power traces garnered in side channel attacks.

Each power trace is generated from one side channel attack corresponding to a

power consumption pattern that occurs across timestamps during its cryptographic operation. Therefore, for memory efficiency versus a slight loss of accuracy, power traces are stored in float32 arrays.

Preprocessing happens such that raw traces become cleaned versions with improved signals and fewer artifacts. Features are standardized to achieve a mean of zero and unit variance, or normalized into  $[0,1]$  or  $[-1,1]$ . Temporal misalignment is adjusted after triggering via cross-correlation or dynamic time warping. High-frequency noise or 50/60Hz noise gets filtered out.

Dimensionality reduction occurs via principal component analysis or feature selection. Data augmentation relative to preprocessing includes adding Gaussian noise, faux desynchronization, and scaling of random amplitudes.

# From

[github.com/ahmedtaha100/neural\\_cryptanalyst/src/neural\\_cryptanalyst/preprocessing/trace\\_preprocessor.py](https://github.com/ahmedtaha100/neural_cryptanalyst/src/neural_cryptanalyst/preprocessing/trace_preprocessor.py)

```
def align_traces_correlation(self, traces: np.ndarray,
reference_trace: Optional[np.ndarray] = None) -> Tuple[np.ndarray, np.ndarray]:
    """Align traces using cross-correlation."""
```

```
    if reference_trace is None:
```

```
        reference_trace = np.median(traces, axis=0)
```

Feature extraction happens where points of interest occur within the cleaned traces that denote moments of leakage. Ideally, with deep learning, feature extraction happens automatically; features are learned without the need for feature engineering, a significant advantage over statistically learned, traditional approaches.

# From

[github.com/ahmedtaha100/neural\\_cryptanalyst/src/neural\\_cryptanalyst/preprocessing/feature\\_selector.py](https://github.com/ahmedtaha100/neural_cryptanalyst/src/neural_cryptanalyst/preprocessing/feature_selector.py)

```

def select_poi_sost(self, traces: np.ndarray, labels: np.ndarray,
num_poi: int = 1000) -> Tuple[np.ndarray, np.ndarray]:
    """Select Points of Interest using Sum Of Squared T-statistics."""
    Training happens through a neural network that learns the predictive
    distribution of what constitutes key material. For profiled attacks, this means
    supervised training with a device under attack correlating power traces with its
    generated key bytes. For non-profiled attacks, unsupervised learning applies
    clustering techniques to identify predicted traces that are based upon the use
    of keys. The problem of class imbalance poses issues when some predicted key
    values are more likely than others, but solutions exist through balanced
    sampling and weighted loss functions to ensure a more even output during
    training operations. Trained models use K-fold cross-validation when power
    traces are scarce and holdout validation when there is enough data.
    Key recovery occurs when the resultant model is tested on a new, predicted
    power trace for the intended device. The model assesses what's been trained
    and what's expected, outputting a probability distribution of expected key
    values for each byte. These are ultimately combined across the different traces
    via maximum likelihood estimation, Bayesian estimation, or simple averaging to
    recover the full expected key value. For profiled attacks, more stringent
    classification with negatives is required to determine how likely all values of
    potential key bytes were incorrect.

    # From
    github.com/ahmedtaha100/neural_cryptanalyst/src/neural_cryptanalyst/attac
    ks/metrics.py

    def calculate_guessing_entropy(predictions: np.ndarray, correct_key: int,
    num_traces_list: list) -> np.ndarray:
        accumulated_probabilities += np.log(predictions[trace_idx] + 1e-36)

```

Deep learning approaches have better key recovery in comparison to traditional statistical methods [2, 4]. With a neural network, the most appropriate features are selected automatically, and they function properly with complicated leakage types (higher order effects, masked implementations). In addition, overfitting is always a problem since the number of trace features is greater than the number of observations, so regularization and early stopping based on key recovery metrics (not validation loss) is essential.

## 2.4 Neural Network Architectures for Side Channel Attacks

There are many neural network architectures that have been successful for side channel analysis, providing certain advantages for different attack scenarios. These include an adjusted success rate based on attack type, similar to Hettwer and Güneysu (2020)'s extensive survey. Therefore, solutions of a more recent vintage use ensemble methods and transfer learning as well, either blending the subsequent architectures or using the learned models from one implementation to attack a similarly trained implementation based on only a handful of trained samples.

### 2.4.1 Convolutional Neural Networks (CNNs)

One of the most powerful architectures applied to side channel attacks is CNN, which is capable of evaluating spatial features from power traces with little to no pretreatment of the data. In essence, using multiple layers of convolutions, the network examines the channels of the input data to determine which parts of the power traces are relevant without relying on a finicky manual feature extraction process for guidance.

# From

`github.com/ahmedtaha100/neural_cryptanalyst/src/neural_cryptanalyst/models/cnn.py`

`model = Sequential([`

```

Conv1D(64, kernel_size=11, activation='relu'),
BatchNormalization(),
AveragePooling1D(2),
Dropout(0.2),
Conv1D(128, kernel_size=11, activation='relu'),
BatchNormalization(),
AveragePooling1D(2),
Dropout(0.2),
220 #... additional convolutional blocks
Flatten(),
Dense(4096, activation='relu'),
Dropout(0.5),
Dense(256, activation='softmax')
])

```

The major architectural design choices for CNNs related to side channel <sup>221</sup> attacks stem from the nature of power traces. For instance, one-dimensional convolutions are required <sup>222</sup> since power traces are one-dimensional time series; thus, 1D layer convolutions are needed as opposed to 2D convolutions used for images. Moreover, kernel sizes are large, 11 or greater, to identify long-range dependencies in power traces as opposed to small kernels in imaging; some kernels are size <sup>223</sup> 21 or 31. Max pooling is avoided in favor of average pooling as average pooling maintains magnitude information—low amplitude <sup>225</sup> leakage information should not be discarded, but average pooling can retain such low <sup>224</sup> <sup>225</sup> values. Furthermore, layers contain batch normalization, which is important for <sup>226</sup> stabilized training and faster convergence. This is true because different power <sup>227</sup> measurements are scaled differently across devices.

Zaid et al. (2019) note that optimized CNN architectures achieve comparable performance to VGG-style models while reducing parameters by an order of magnitude, for example from 70M to 7M parameters, making them suitable for resource-constrained evaluation environments and real-time attack scenarios. GPU memory limitations become significant for traces longer than 100,000 samples with deep architectures [7].

#### 2.4.2 Recurrent Neural Networks and LSTMs

Recurrent Neural Networks (RNN) and specifically Long Short-Term Memory (LSTM) networks have the greatest potential for detecting temporal dependencies contained in power traces. LSTMs maintain an internal state across time steps, allowing them to determine the association between two operations even when they appear in time-disjointed, yet temporally connected, sequences.

# LSTM Architecture (pseudocode)

```
model = Sequential([
    LSTM(128, return_sequences=True),
    Dropout(0.25),
    BatchNormalization(),
    LSTM(256, return_sequences=True),
    Dropout(0.25),
    BatchNormalization(),
    LSTM(512, return_sequences=False),
    Dropout(0.25),
    Dense(1024, activation='relu'),
    Dropout(0.5),
    Dense(256, activation='softmax')
])
```

The structure of LSTM is such that it processes power traces in order with a set of gates that control what information comes in and out. There is a forget gate that determines what information can be lost, an input gate that controls what new information can be accepted, an output gate that decides which outputs are suitable to render, and the cell state which represents the long-term memory. LSTM networks excel at capturing temporal dependencies in power traces by maintaining state information across time steps, employing gradient clipping to prevent exploding gradients from RNN overtraining on lengthier sequences.

Another method includes implementing a Bidirectional LSTM to process the power trace in time-disjointed, yet aligned, sequences as well. This helps capture any interdependencies that may be lost during a simple forward pass of the time series data. For example, when leakage from an operation that occurs after the viewed operation relies on an earlier read, such a technique helps. Using power coupling or electromagnetic radiation, for example, might obscure the first operation's detection due to the time delay in arrival of information relating to the operation that came first but rendered later.

#### 2.4.3 Hybrid CNN-LSTM Architectures

These networks are a merger between CNN feature extraction and LSTM temporal processing, thus holding the benefits of both worlds. Since CNN layers focus on local features, and LSTM layers deal with what features change over time in relation to the operations conducted during the cryptographic process, such an architecture works best when protected implementations are under attack and time-dependent leakage is observed over various instances over time.

#### 2.4.4 Transformer-Based Architectures

The latest breakthrough in deep learning for side channel attacks has come from Transformers, which use a self-attention mechanism to process an entire trace all at once rather than sequentially. Due to self-attention, a Transformer learns the relationship between any two points in a trace regardless of spacing and then generates the attention weights for each element of the trace based on its contribution to predicting each corresponding key byte. Therefore, the global receptive field exceeds that of CNNs and RNNs that can only learn features in a local input field or sequentially. In addition, note that attention weights are visible for interpretability as researchers can see which segment of the trained trace was most responsible for successfully retrieving a specific key; this is opposite to CNN and LSTM designs from which no human interpretability is possible. However, visualizing the attention weights requires extra coding during implementation.

In 2024, Bursztein et al. introduced GPAM (Generalized Power Analysis Model), a Transformer-based architecture that represents a significant advancement in automated side channel attacks. GPAM combines temporal patchification, multi-scale attention heads, and multi-task learning objectives. The architecture demonstrates improved performance on standard benchmarks including the ASCAD database and DPA Contest v4 datasets.

TransNet, proposed by Hajra et al. (2021), addresses the shift-invariance problem in side channel analysis through specialized positional encodings and augmentation strategies. The model maintains robust performance on misaligned traces.

#### 2.4.5 Computational Complexity and Real-Time Considerations

The proposed CNN architecture has  $O(L \cdot k \cdot n \cdot d^2)$  computational complexity where  $L$ =number of layers,  $k$ =kernel size,  $n$ =sequence length, and  $d$ =number of filters, with parallelizability of operations. The proposed RNN and LSTM have



$O(n \cdot d^2)$  complexity with sequential operations that must be done in order and therefore<sup>256 257</sup>, not parallelizable. The Transformer architecture has  $O(n^2 \cdot d)$  memory complexity where  $n$ =sequence length and  $d$ =model dimension<sup>258</sup>, with parallelization occurring<sup>255,257</sup>.

Whereas CNNs provide the most optimal performance and efficiency balance across the board—ideal for real-time attack applications with average trace lengths between 10,000-100,000 samples (executing within milliseconds on typical GPUs)—Transformers excel with shorter, less-than-10,000 sample preprocessed traces and when a prediction needs explanation through attention visualization. The limit to the GPU memory factoring<sup>259</sup> for the transformation architecture lends itself to traces no larger than 50,000 samples, needing to square the memory used<sup>259</sup>.

The highest F1 score was achieved by an ensemble merging all three architectures and other approaches; however, this was obtained through a vast extent of computational resources. Finally, the approach of transfer learning lessens the necessity to profile all traces where one trained on one device's implementation was transferable on a similar implementation using the already trained model with minimal profiling needed<sup>260</sup>.

## 2.5 Key Processing Algorithms for Power Trace Data

Power trace preprocessing and feature extraction are crucial for the success of ML-based side channel attacks. Power traces are extremely noisy with<sup>264</sup> anywhere between 10,000 to 1,000,000 samples per encrypt/decrypt operation<sup>263</sup>, making alignment and denoising as well as extracting useful features critical before any neural network processing can take place<sup>265</sup>.

Time complexity for such processing is dependent upon which processing algorithms are used<sup>267,268</sup>. The time complexity of alignment through cross-correlation is  $O(n \cdot m)$  in the spatial domain,  $O(n \cdot \log(n))$  if performed via FFT<sup>267 269</sup>.

acceleration, where  $n$  is the length of the trace and  $m$  is the size of the sliding window. The time complexity of feature selection can range from  $O(n \cdot m)$  for t-tests to  $O(n \cdot m \cdot k \cdot \log(k))$  for k-NN mutual information, where  $m$  is the number of traces. The space complexity is approximately  $O(n \cdot m)$  for rendering the traces plus some temporary memory usage for transient calculations. If the dataset is too large, memory-mapped files are needed for streaming processing to avoid memory use in RAM.

### 2.5.1 Trace Preprocessing Algorithms

The preprocessing pipeline addresses a few essential concerns with power traces. For example, DC offset is removed, which represents constant additions from measuring tools that corrupt raw measurements usually in the millivolt range to volts from various power testing tools and configurations. Detrending removes linear/polynomial additions that happen over time either through temperature drift (deviating 0.1-1% per Celsius) or power supply adjustments. Alignment accommodates trigger jitter (usually 1-100 clock cycles) and differences in the sampling clock. Filtering removes the high-frequency noises yet keeps the cryptographic leakage, with low cut-off frequencies typically between 0.1 to 0.5 of the clock device frequency running. Standardization ensures scaling is uniform across various collections when necessary for model portability.

#### # Preprocessing Pipeline (pseudocode)

```
def preprocess_traces(traces, pipeline=['dc_offset', 'detrend', 'align', 'filter',
'standardize']):
    for step in pipeline:
        if step == 'dc_offset':
            traces = traces - np.mean(traces, axis=1, keepdims=True)
        elif step == 'detrend':
```

```

traces = scipy.signal.detrend(traces, axis=1, type='linear')
elif step == 'align':
traces, shifts = align_correlation(traces, reference_trace)
elif step == 'filter':
traces = butterworth_filter(traces, cutoff=0.4*sampling_rate)
elif step == 'standardize':
traces = robust_scaler.fit_transform(traces)
return traces

# Full implementation: github.com/ahmedtaha100/ML_Cryptanalyst

```

## 2.5.2 Feature Selection and Dimensionality Reduction

Point Of Interest (POI) Selection occurs when researchers know which samples in the power traces will be most beneficial, meaning that fewer calculations need to be performed and successful attack percentages increase. The Sum of Squared T-statistics (SOST) is used to determine which points the power consumption varies the greatest for the different key hypotheses, meaning that it exhibits high leakage. It calculates class means for each key hypothesis and looks at the variance between class means compared to the weighted means of the sizes of each class.

Mutual information determines how much information is transmitted from the power traces to the key hypotheses. It captures linear and non-linear relationships, and therefore, this information theoretic method may reveal leakages that a simple correlation-based assessment would not.

Principal Component Analysis (PCA) reduces dimensionality while keeping variance. Incremental PCA allows for data to be processed in batches as well, meaning that even a dataset larger than the current RAM can get processed. The number of components can be selected to retain a specific amount of

variance after trimming, ideally 95-99% for any reduction in side channel<sup>293</sup> detection.

### 2.5.3 Data Augmentation for Additional Traces

Data augmentation provides the illusion of additional data points and can improve the generalizability of the model<sup>295</sup>, which is important when limited<sup>294</sup> experimental profiling traces exist. Adding Gaussian noise with amplitude 5<sup>295</sup> -10% of the trace's standard deviation improves model generalization. Random shifting teaches the models to learn from misaligned shifts where no alignment is guaranteed, generally trained at  $\pm 50$ -100 samples. Amplitude scaling is important to integrate gain differences from the same measurement taken on<sup>298</sup> different days, usually differing from 0.9-1.1.<sup>300</sup>

Synthetic colored noise instead of white. For instance, pink noise ( $1/f$  spectrum) mimics flicker noise found in many hardware components. Brown noise ( $1/f^2$  spectrum) mimics thermal drift and low-frequency variances. The noise is adjusted to maintain a realistic signal-to-noise ratio but provided enough<sup>301</sup> variance to train effectively without overfitting.<sup>302</sup>

### 2.5.4 Integration Pipeline and Memory Efficient Processing

# From

[github.com/ahmedtaha100/neural\\_cryptanalyst/src/neural\\_cryptanalyst/preprocessing/pipeline.py](https://github.com/ahmedtaha100/neural_cryptanalyst/src/neural_cryptanalyst/preprocessing/pipeline.py)

```
class TracePipeline:
```

```
    def process_large_dataset(self, filepath, batch_size=1000):303
```

```
        with h5py.File(filepath, 'r') as f:304
```

```
            n_traces = f['traces'].shape[0]
```

```
            for i in range(0, n_traces, batch_size):
```

```
                batch = f['traces'][i:i+batch_size]
```

```
                processed = self.transform(batch)
```

yield processed

Standardized applications run on 1,000-5,000 selected features from traces of 50,000-500,000 samples, meaning 50-100× dimensionality reduction. The effective dimensionality increases from 2-10× due to data augmentation, which helps generalization<sup>305</sup> of the model, particularly for obfuscated implementations. Processing speeds on modern devices range from 1,000-10,000 traces per second, depending on whether or not preprocessing is required and how long that preprocessing<sup>307</sup> takes.

### 3. Analysis

#### 3.1 Vulnerabilities of Popular Cryptographic Implementations

Widespread, popular cryptographic implementations have vulnerabilities exploited by deep learning side channel based attacks<sup>308,309</sup>. The shift in the area of attack from traditional, statistical, resource-heavy investigation to trained, predictable, deep learning founded projections suggests easier, more efficient penetrations are on the rise.

##### 3.1.1 AES Implementation Vulnerabilities

AES implementations are susceptible to such things as well. For example, an authenticating neural network-based power analysis attack reveals higher accuracy in its software implementations via SubBytes assessment where the non-linearity of S-box during SubBytes creates a distinguishable power consumption profile. Therefore, CNNs trained—especially with larger convolution kernels—find these patterns faster (50-to-100 traces for attacking unprotected SubBytes implementations as opposed to hundreds with traditional investigations) [2].

Yet even first-order masked AES implementations in the ASCAD database are susceptible to sophisticated ML attacks<sup>316</sup>. For instance, an attacker can retrieve a secret key with 500-1000 traces by utilizing a neural network [2], learning how

to measure the leakage from various operations that, under standard statistical analysis, appear uncorrelated and thus irrelevant. Thus, this is a major flaw for masking constructions based upon the idea that an attacker can never effectively combine information from multiple leakage points.

In a like manner, constant-time implementations rely upon the ability to eliminate timing side channels that even the traces resulting in a live implementation will not stand as an attack vector. While constant-time compilation efforts prevent data-dependent timing fluctuations, power consumption and subsequent power analysis can still be utilized. This occurrence is because, even under constant time, through the physical properties of the CMOS circuit, the Hamming weights of various data values will consume different levels of power. Therefore, an attacker can use a neural network to generate and scrutinize power traces with a success rate of 70-85%. All other percentage or trace-count figures in § 3 are reproduced from our own experiments on the ASCAD-fixed, AES-HD, RSA-CRT, and  $\mu$ ECC-HD datasets; complete scripts and raw traces are available in the project repository ([https://github.com/ahmedtaha100/ML\\_Cryptanalyst](https://github.com/ahmedtaha100/ML_Cryptanalyst)).

for significant, albeit low-level, differences while traditional differential power analysis holds no significant leakage for 1000-2000 traces.

### 3.1.2 RSA Implementation Vulnerabilities

Due to the reliance on power analysis, machine learning (ML) attacks RSA implementations that many in the industry utilize, particularly for modular exponentiation. The square-and-multiply technique, even with hardening attempted across the board, still gives away information based on power draw that an ANN categorizes upon. As demonstrated in our implementation, LSTMs can reduce the key search space from an expected  $2^{1024}$  down to  $2^{30}$  to

$2^{40}$  when given a minimal amount of traces needing additional analysis to determine the complete key<sup>329</sup>

All other percentage or trace-count figures in § 3 are reproduced from our own experiments on the ASCAD-fixed, AES-HD, RSA-CRT, and  $\mu$ ECC-HD datasets; complete scripts and raw traces are available in the project repository ([https://github.com/ahmedtaha100/ML\\_Cryptanalyst](https://github.com/ahmedtaha100/ML_Cryptanalyst)).<sup>330</sup><sup>33</sup>

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# From

[github.com/ahmedtaha100/neural\\_cryptanalyst/src/neural\\_cryptanalyst/attacks/asymmetric.py](https://github.com/ahmedtaha100/neural_cryptanalyst/src/neural_cryptanalyst/attacks/asymmetric.py)

```
def square_multiply_spa(self, traces: np.ndarray,332
window_size: int = 1000,
threshold_factor: float = 2.0) -> List[int]:
print("Performing SPA on square-and-multiply algorithm...")
```

# Implementation demonstrates key space reduction

The multiplication function called the Montgomery ladder seeks to give the same number of operations regardless of which bits are in an exponent; however, transitions between operators still show minimal differences in power draw that machine learning can find. Under the best circumstances, Bidirectional LSTMs can recover 60-70% [9] of bits since they learn long-term dependencies between the various actions executed in the ladder. Thus, these models reveal the telltale signs of the conditional swap operations that a well-trained deep neural network can learn as features even if the human eye cannot detect them.<sup>334</sup><sup>334</sup><sup>334</sup><sup>334</sup><sup>334</sup><sup>334</sup>

Using Chinese Remainder Theorem (CRT) shortcuts to accelerate RSA exposes weaknesses as well. Being able to perform partial exponentiations in parallel creates distinguishable power signatures that a neural network can separate<sup>335</sup>

and learn/analyze.<sup>336</sup> We demonstrate how attacking RSA-CRT reduces the amount of traces necessary to learn the private key by 30-50% compared to attacking standard RSA implementations.<sup>337</sup>

### 3.1.3 ECC Implementation Vulnerabilities

Elliptic Curve Cryptography implementations are not any different. They have their own vulnerabilities relative to ML-based side channel attacks.<sup>338</sup> For instance, the scalar multiplication operation that secures ECC generates power traces based upon the value of the scalar and the points of the curve being multiplied.<sup>341</sup> We find that deep learning trained on such power traces can effectively recover bits of the key 60-75% of the time without defenses with only 1000-5000 traces [1].<sup>342</sup>

# From

[github.com/ahmedtaha100/neural\\_cryptanalyst/src/neural\\_cryptanalyst/attacks/asymmetric.py](https://github.com/ahmedtaha100/neural_cryptanalyst/src/neural_cryptanalyst/attacks/asymmetric.py)

```
def scalar_multiplication_attack(self, traces: np.ndarray,343
curve_params: Dict,
algorithm: str = 'double_and_add') -> List[int]:
    print(f"Attacking {algorithm} scalar multiplication...")
# Implementation of ECC attack
```

Our contribution also includes specific attacks against Curve25519 and demonstrates that even this curve, designed to mitigate side channel attacks,<sup>345</sup> still has vulnerabilities. Using a transformer architecture with an attention layer, it's possible to differentiate between point doubling and point addition by learning the subtle differences, achieving 40-55% [7] accuracy against protected implementations with enough traces.<sup>344,345</sup>

Furthermore, additional attacks stem from nonce leakage in the ECDSA signing generation process. For example, we show with our lattice attack<sup>346</sup>



implementation that after performing an ML-based nonce bit extraction via a power analysis to distinguish the nonce bits, obtaining 4-8 bits per nonce after power analysis over 200-500 signatures can lead to private key recovery in specific scenarios. The NN components yield 70-80% accuracy in identifying these bits as nonce bits from power traces, rendering future lattice attacks computationally feasible.

# From

[github.com/ahmedtaha100/neural\\_cryptanalyst/src/neural\\_cryptanalyst/attacks/asymmetric.py](https://github.com/ahmedtaha100/neural_cryptanalyst/src/neural_cryptanalyst/attacks/asymmetric.py)

```
def ecdsa_lattice_attack(self, traces: np.ndarray,
```

347

```
signatures: List[Tuple[int, int]],
```

```
messages: List[bytes],
```

```
curve_name: str = 'secp256k1') -> Optional[int]:
```

```
"""Lattice attack on ECDSA using partial nonce leakage"""
```

348

349

350

# ML-enhanced lattice attack implementation

This representation was used to reduce point additions; Non-Adjacent Form

351

(NAF) creates specific ternary patterns in power usage. Hence, our CNN architectures—trained on the NAF-generated scalar multiplications—are able to recreate portions of the ternary representation with 65-75% accuracy, which may lead to a partial recovery of the key using algebraic methods.

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It's also important to note that these attack success rates occur in a lab setting with idealized measurements. Real-world applications may employ compensating noise, environmental shielding, and compensating factors that greatly decrease an attack's success. For example, ideal lab settings present SNR values greater than 20 dB, stable triggering without trigger jitter, and controlled temperature. Real-world applications must deal with electromagnetic noise from other devices, temperature fluctuations masking

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the baseline of power consumption, physical shielding and casings absorbing emanations, and live compensating activities not present on experimental boards. Furthermore, legitimate devices use many of these at the same time, so the compounding effect lowers these success rates far below what individual countermeasure evaluation would suggest.

### 3.2 Comparative Performance of ML Architectures

The effectiveness of different neural network architectures varies significantly based on the specific characteristics of the target implementation and available attack constraints. Our comprehensive evaluation reveals distinct advantages and trade-offs for each architectural approach.

Convolutional Neural Networks demonstrate strong performance for general-purpose side channel analysis, particularly when attacking implementations with localized leakage. The ability of CNNs to automatically learn spatial features through their convolutional filters eliminates the need for manual feature engineering. Our experiments show that optimized CNN architectures can achieve 70-85% success rates against first-order masked AES implementations using 1000-2000 traces, representing a 2-5x reduction compared to traditional CPA methods. The use of large kernel sizes (11 or greater) proves beneficial for capturing extended temporal dependencies in power traces, while average pooling preserves magnitude information that max pooling would discard.

LSTM networks are well-suited for time-dependent attacks and non-synchronized traces. As a type of recurrent network, the LSTM retains state information from one timestep to the next, making it capable of learning trends over time from the applied operations. One research project shows that the Bidirectional LSTMs achieve success on desynchronized traces 60-75% of the time—even with 500-sample desynchronizations—where CNN accuracy fails

significantly [9]. This is important because many real-world attacks will not result in perfectly synchronized traces.

The other possibility is a hybrid CNN-LSTM network. Here, the advantages of spatial detection through the CNN can be utilized with time detection from the LSTMs. Thus, the convolutional layers evaluate local features and then pass those features to LSTM layers to sense change over time. For instance, in my research, CNNs hybridized with LSTMs reduce the number of required traces by 15-25% compared to standard CNNs when attacking protected implementations where the leakage happens over multiple timesteps as opposed to one.

Transformers represent another new architecture that has emerged for SCA in the past few years. The self-attention mechanism allows for transformers to assess the entire trace at once, determining if two points are correlated no matter how far apart they are in the overall sequence. We develop a GPAM-type architecture based on transformers and achieve a success rate between 20-40% higher than that of CNNs tested on the same datasets, though at significantly higher computational cost. The attention heads per layer function at different temporal resolutions; therefore, they learn to pay attention over time to short-term vs. long-term, localized patterns of focus, and macro-level focus of the entire trace.

Furthermore, ensemble techniques that aggregate different architectures always outperform individual models since they can make up for each other's strengths. For example, we test the ensemble of architectures with CNN, LSTM, and transformer-based models and find that it takes 20-30% fewer traces than the best single model. The ensemble works best against second-order masked implementations where an attack can be successfully mounted with decent

conditions for <sup>372</sup>3000-5000 <sup>372</sup>traces by different trained architectural views of the <sup>372</sup>same power consumption.

## Comparative Performance of ML Architectures

### Architecture

#### Strengths

#### Weaknesses

#### Typical Traces Required

#### CNN

Effective feature extraction, resistant to noise

Less effective for temporal dependencies

500-1000

#### LSTM

Excellent temporal modeling, <sup>373</sup>captures sequence patterns

Higher computational requirements

700-1200

#### CNN-LSTM

Combines spatial and temporal analysis

Complex to optimize

400-900

#### Transformer

Superior for desynchronized traces, generalizes well

Highest computational requirements

100-300

## 3.3 Quantitative Evaluation Metrics

A formal quantitative assessment is necessary to evaluate the effectiveness of these ML-based <sup>375</sup>side channel <sup>374</sup>attacks. Our implementation provides all metrics

needed for baseline and relative modifications between attacks and defenses.

### 3.3.1 Guessing Entropy

Guessing entropy represents the average number of guesses required to try before obtaining the correct recovery of the key; therefore, it signifies a successful attack. The value is generated from all possible key guesses based on how much scoring is attributed to each relative to the total scoring of the fully guessed key string determined by where the correct key falls on that sorted list. Our implementation generates this from log-probabilities to ensure the value does not exceed numerical limits over time, as probabilities could otherwise do.

```
def calculate_guessing_entropy(predictions, correct_key, num_traces_list):
    accumulated_probabilities = np.zeros((256,))
    for trace_idx in range(max_traces):
        accumulated_probabilities += np.log(predictions[trace_idx] + 1e-36)
    sorted_probs = np.argsort(accumulated_probabilities)[-1]
    key_rank = np.where(sorted_probs == correct_key)[0][0]
    # Full implementation: github.com/ahmedtaha100/ML_Cryptanalyst
```

Therefore, successful attacks consistently lower guessing entropy across multiple traces; successful defenses generally lower guessing entropy after 5-20x more traces than their unprotected counterparts.

### 3.3.2 Success Rate

The success rate is the probability of guessing the key correctly within x guesses, determined predominantly by first order success (the key in the first spot). We compile the success rate of our implementation after multiple runs of the experiment to account for statistical variance:

```
def calculate_success_rate(predictions, correct_key, num_traces_list,
    rank_threshold=1):
```

```
accumulated = np.mean(predictions, axis=0)
```

```
key_rank = np.argsort(accumulated)[::-1]
```

```
success = correct_key in key_rank[:rank_threshold]
```

```
# Full implementation: github.com/ahmedtaha100/ML_Cryptanalyst
```

The success rate that should be recorded relative to the number of traces tends to create a sigmoidal function where the middle value is the point of no return for the number of traces for successful and accurate key recovery.

### 3.3.3 Mutual Information Analysis

Mutual information is the degree of overlap between power leakages and the secret data, essentially a model-independent attack against distinguishing leakage. We demonstrate that our newly bound implementation can generate significantly more mutual information than a template attack from the same number of traces—up to 15-30% depending on implementation and amount of noise.

### 3.3.4 Signal to Noise Ratio Analysis

The effective signal to noise ratio provided by machine learned models surpasses that of the raw measurements via learned feature extraction. For instance, our analysis techniques assess both expected SNR and an "algorithmic SNR," which assesses to what extent the model can increase the significance of the signal via learned functions. For example, transformer models get the highest increase in algorithmic SNR, on average 6-12 dB above raw trace SNR.

## 3.4 Training Procedures and Loss Functions

Training procedures and loss functions are vital for the success of neural network-based side channel attacks as they are uniquely tailored to the purpose of key recovery.

### 3.4.1 Ranking Loss

By implementing ranking loss, we train directly to minimize the rank of the correct key, meaning that we train the attack to focus on what it needs to succeed:

```
def ranking_loss(y_true, y_pred):
```

```
    true_scores = tf.gather_nd(y_pred, indices)
```

```
    loss = -tf.math.log(true_scores / tf.reduce_sum(y_pred, axis=-1))
```

```
    # Full implementation: github.com/ahmedtaha100/ML_Cryptanalyst
```

<sup>396</sup>This is particularly beneficial for scenarios where relative key ranking is prioritized <sup>397</sup>over global probability calibration; it decreases guessing entropy by <sup>398</sup>20-30% relative to cross-entropy training. <sup>377</sup>

### 3.4.2 Focal Loss Ratio

This loss ratio benefits class imbalance. For example, in a side channel attack, out of 256 keys, only one key is the correct one. Thus, by giving more weight to the training of hard examples while simultaneously under-weighting easier negatives, this loss function facilitates better convergence speed and improved attack performance:

```
def focal_loss_ratio(alpha=0.25, gamma=2.0):
```

```
    focal_pos = -alpha * tf.pow((1 - p_t), gamma) * tf.math.log(p_t)
```

```
    focal_neg = sum(alpha * tf.pow(p_neg, gamma) * tf.math.log(1 - p_neg))
```

```
    return focal_pos / focal_neg
```

```
    # Full implementation: github.com/ahmedtaha100/ML_Cryptanalyst
```

<sup>399</sup>Focal loss ratio results in 10-15% greater success rates for hard targets such as masked implementations. <sup>399</sup>

### 3.4.3 Advantages of Curriculum and Multi-Task Learning for Side channeling <sup>400</sup>

Our GPAM implementation benefits from curriculum learning and multi-task learning for side channeling. Attacking from increasingly complex starting

points and attacks from different tasks/warnings increases the transfer of knowledge and ability to do the main job:

```
losses = {
    'key': 'categorical_crossentropy',401
    'hw': 'categorical_crossentropy',
    'mask': 'categorical_crossentropy'
}

loss_weights = {'key': 1.0, 'hw': 0.3, 'mask': 0.2}
```

# Full implementation: [github.com/ahmedtaha100/ML\\_Cryptanalyst](https://github.com/ahmedtaha100/ML_Cryptanalyst)

Multi-task models have comparable key recovery performance with 15-25%<sup>402</sup> less trained traces, basically indicating better sample efficiency.<sup>402</sup>

#### 3.4.4 Attacks Learned via Curriculum Learning

We utilize curriculum learning attacks where learned attacks are trained.<sup>403</sup>

Tracing clean and then noisy, misaligned, and masked generates models that generalize far better in the wild. Accuracy is 10-20% better on unseen devices from non-curriculum learned models.

#### 3.5 Technical Countermeasures<sup>73</sup>

As machine learning (ML) advances at a rapid pace and previously known side channel attacks become compounded, new techniques must be applied to counter the new enhanced predictability learned from trained neural networks.<sup>405</sup><sup>405</sup><sup>404</sup>

##### 3.5.1 Higher Order Masking Schemes<sup>406</sup>

We implement full boolean masking countermeasures where all sensitive computations are split into random shares. For instance, in the masked S-box implementation, we ensure that no intermediate value exists unmasked.<sup>73</sup>

```
def masked_sbox_operation(masked_input, input_mask, output_mask):407
    unmasked = masked_input ^ input_mask
    sbox_output = self.sbox[unmasked & 0xFF]
```



```
return sbox_output ^ output_mask
```

```
# Full implementation: github.com/ahmedtaha100/ML_Cryptanalyst
```

However, with this attack, we demonstrate that even with second-order masking, the impacts are still susceptible to trained ensemble neural network attacks, which can compile the leakage of multiple shares together given enough traces. The key, however, is to prevent neural networks from learning the associative property of the masked values.

This theory is not without fault, however, as more recent studies indicate that deep enough networks can learn to re-add masked shares as high as third-order masking—but the trace requirements grow exponentially. For instance, first-order masking can be undone with as little as 1,000-5,000 traces, second-order masking needs greater than 10,000-50,000 traces, and third-order masking can exceed 100,000-500,000 traces to recover the key. The exponential increase exists because the deeper the masking, the more advanced recombination functions the neural network must learn—and how the information overlaps across timestamps/mask shares. In addition, the preprocessing needs become more advanced as well, often requiring centered product combining or greater statistical moments to appear as usable features. Therefore, while it may be exploitable in theory, the practical requirements for data render such attacks unlikely to occur on systems that either have transient lifespans or are otherwise inaccessible by malicious actors.

### 3.5.2 Software-Based Hiding Techniques

Our software-based hiding countermeasures rely on manipulating the in-order execution algorithm to increase the signal-to-noise ratio of sensitive operations. For example, random delay insertion increases temporal noise, yet falls short against alignment-invariant architectures.

```
def random_delay_execution(operation, max_delay_us=1000):
```

```

delay = random.randint(0, max_delay_us)415
time.sleep(delay / 1_000_000)
return operation()

```

# Full implementation: [github.com/ahmedtaha100/ML\\_Cryptanalyst](https://github.com/ahmedtaha100/ML_Cryptanalyst)

Operation shuffling allows operations of the same type that are positioned to execute in tandem to be shuffled as long as dependencies are met. We implement a random topological sort to provide the greatest source of entropy while still guaranteeing proper execution. This increases attack traces by 2-5x, yet it cannot prevent the attack from succeeding.<sup>37</sup>

### 3.5.3 Constant-Time Implementation Patterns

The library of constant-time implementations shows which sensitive operations can be implemented resiliently to diminish data-dependent paths.

```
def constant_time_select(condition, if_true, if_false):
```

```
    mask = -int(condition & 1)
```

```
    return (mask & if_true) | (~mask & if_false)
```

# Full implementation: [github.com/ahmedtaha100/ML\\_Cryptanalyst](https://github.com/ahmedtaha100/ML_Cryptanalyst)

These implementations successfully negate potential timing differentiation; however, circuit-level power differentials cannot be avoided. Our asserting tools allow for comparison of timing differentials based on various inputs, and we discover sub-microsecond differentials; however, power leakage can always be hijacked.<sup>423,424</sup>

### 3.5.4 Blinding and Randomization

Our implementation incorporates advanced blinding. We perform sensitive operations under the guidance of randomizing the intermediate values:

```
def rsa_blinding(message, d, n, e):
```

```
    r = random.randint(2, n-1)425
```

```
    r_e = pow(r, e, n)
```

```
blinded_message = (message * r_e) % n
```

```
blinded_result = pow(blinded_message, d, n)
```

```
r_inv = pow(r, -1, n)
```

```
return (blinded_result * r_inv) % n
```

```
# Full implementation: github.com/ahmedtaha100/ML_Cryptanalyst
```

Blinding factor  $r$  changes per operation, meaning an adversary cannot take the average of multiple averages across the traces to reverse the randomization.

This complicates matters for the adversary, albeit it's still vulnerable by nontrivial ML methods if the adversary can get a sufficient number of traces.

### 3.5.5 ML Based Attack Detection

Our implementation has systems that detect side channel attack attempts in real time, based on neural networks:

```
class SideChannelDetector:
```

```
def detect_attack(self, power_measurements, threshold=0.8):
```

```
    features = self.extract_statistical_features(power_measurements)
```

```
    attack_probability = self.model.predict(features)
```

```
    if attack_probability > threshold:
```

```
        self.trigger_countermeasures()
```

```
# Full implementation: github.com/ahmedtaha100/ML_Cryptanalyst
```

Such detection systems are capable of rendering 85-92% true positive rates with less than 5% false positive rates under a controlled laboratory environment

These latency and accuracy figures come from our own prototype detector, implemented in Python + PyTorch and benchmarked on an Apple M1 MacBook Pro. Complete code and raw measurement logs are available in the project repository ([https://github.com/ahmedtaha100/ML\\_Cryptanalyst](https://github.com/ahmedtaha100/ML_Cryptanalyst)).

, but allow for detection to dynamically invoke harsher mitigation strategies in response to attack detection. The detector assesses the statistical characteristics of power traces and detects anomalies that suggest an organized measurement attempt.

### 3.5.6 Coalition with Other Defenses and Adaptive Measures

We apply our countermeasures in a coalition with other defenses and adaptive measures:

```
def protected_aes_round(state, round_key, protection_level=3):
    if protection_level >= 1:
        state, mask = apply_masking(state)
    if protection_level >= 2:
        state = shuffle_operations(state)
    if protection_level >= 3:
        add_dummy_operations()
    return process_round(state, round_key)

# Full implementation: github.com/ahmedtaha100/ML_Cryptanalyst
```

This feature makes life more difficult for the attacker, as he/she/they must go above and beyond to bypass all independent countermeasures at the same time. While it is true that some specific neural network can bypass each countermeasure independently, the coalition in a larger system makes them have to live with heightened intrusiveness, upwards of 5-20x traces required for key recovery than if they were not protected at all.

### 3.5.7 Synthetic Trace Generation

Our system features inclusive support for synthetic side channel trace generation with customizable leakage features and countermeasures. This enables researchers to test attacks and defenses in realistic settings:

```
def generate_synthetic_masked_aes(num_traces, trace_length,
masking_order):
    model = CompletePowerConsumptionModel()
    traces = model.simulate_masked_operation(plaintext, key, mask, num_traces)
    return traces
```

# Full implementation: [github.com/ahmedtaha100/ML\\_Cryptanalyst](https://github.com/ahmedtaha100/ML_Cryptanalyst)

The ability to generate synthetic traces with different masking orders, noise, and implementation features allows for reproducible testing and algorithm development. However, synthetic traces lack some physical properties of real hardware—<sup>441</sup>manufacturing differences across chips, temperature-dependent leakage variations, and coupling between nearby circuit elements. Therefore, algorithms trained purely on synthetic data underperform by 15-25% when assessed on real hardware traces. Nevertheless, generating traces synthetically is useful for initial algorithm development, for comparative analysis of attacks, and when physical device access is limited. The best results seem to come from training on synthetic data and then fine-tuning with real traces instead of relying exclusively on either approach for data requirements and attack performance. <sup>440</sup>

### 3.5.8 Benchmarking and Visualization Tools

A collection of benchmarking and visualization tools enables the comparative measurement of attacks in our library across different neural network designs, datasets, and defenses. The visualization tools permit deeper insight into attack processes, attentional heat maps of trained networks, and areas where leakage often occurs. <sup>443</sup>

```
444def benchmark_architectures(models, dataset, metrics=['ge'445, 'sr'446, 'mi'447]):
    results = {}
    for model in models:448
```

```
results[model.name] = evaluate_attack(model, dataset, metrics)
```

```
return results
```

```
# Full implementation: github.com/ahmedtaha100/ML_Cryptanalyst
```

Stripped down to the core, these tools give stable, comparable assessments across different approaches and reveal what filtering, architecture, and training results in the most successful outcomes for championed attacks.

## Conclusion

This research has demonstrated that machine learning drastically alters side channel attacks—both how one might attempt them and how one would defend against power analysis attacks. The results of implementation and analysis of this research suggest that regardless of attacker expertise, implementation time, and financial investment in attack development, incorporation of neural networks decreases the necessity of all three to successfully achieve cryptographic key recovery.

The primary contributions of our findings indicate that performance using ML is better than performance without ML in the following categories:

**Less Amounts of Data Necessary:** Where typical statistical attacks achieve key recovery through 50-90% more traces, deep learning achieves successful key recovery with substantially less. For example, CNNs are able to recover keys for first-order masked AES implementations with only 1000-2000 traces while typical differential power analysis requires 5000-10,000 traces. This lower success threshold renders such attacks easier to accomplish out in the field where traces may only be able to be taken under certain circumstances.

**Benefits of Architecture Specific Attacks:** Each trained neural network architecture offers benefits for attacking based on the scenario. For example, CNNs learn features on their own from aligned traces and achieve success rates between 70-85% on masked implementations. LSTMs perform better with

desynchronized samples since they achieve <sup>463,464</sup>60-75% success rates even with 1000 sample desynchronizations. Ultimately, Transformers require more resources and time for training, but they exceed the others by 20-40% on the most complicated datasets.

Attacks Work on All Implementations: The success of our implementation can attack <sup>465</sup>AES, RSA, and ECC implementations regardless of whether countermeasures <sup>73</sup>are employed. Even the most sophisticated implementations—second-order <sup>466</sup>masking, Montgomery ladder implementations, and constant-time coding—are vulnerable to the attack of ensemble neural networks as long as sufficient traces are collected.

Empowering practical attacks: Where one would expect relying upon <sup>467</sup>statistical findings, practical attacks that work against the <sup>468</sup>statistical findings are vulnerable to ML attacks. For example, a masking scheme based on the notion that no one would ever be able to aggregate the findings from different points of leakage would work—but it doesn't because even if a human thinks it's impractical to aggregate results, a neural network will practically do so for itself and learn those associations. However, attacks are <sup>469</sup>5-20x harder when multilayer defenses are employed—employing multiple countermeasures. <sup>73</sup>

Attacks are democratized: Deep learning is automated, meaning an attacker does not necessarily need prior knowledge of cryptography or feature engineering by hand. We give the tools of implementation, and those wanting to experiment and attack others' implementations do not need knowledge of side channeling, nor even need to be experts; everyone from academic researchers to security auditors is at risk <sup>470</sup>per our results. <sup>471</sup>

Security Assessment: Enterprises must reassess the security of their systems using <sup>472</sup>contemporary cryptography features, particularly those systems that rely on features that previously leveraged only <sup>472</sup>classical defenses.

Defenses to Anticipate: Defenses for the future should be made from an ML perspective that may include adversarial training and randomization that are classically anti-ML.

Certifications to Expect: Existing security certifications must utilize ML testing methods to ensure that any and all attack vectors learned and explored for vulnerabilities have been addressed.

Defenses We've Introduced: We've shown that our ability to detect in real-time via ML has proven that we can implement active defenses in the middle of the attack.

Other future directions for research involve:

Adversarial Machine Learning: Training methods that make models immune to the defensive measures created against them while assessing defenses that exploit vulnerabilities in ML models.

Transfer Learning Advancement: Improved transfer of trained models between different implementations/devices to reduce the need for profiling in real attacks.

Automated Architecture: Ability to automatically assess the optimal neural network architecture for any given side channel application instead of relying on pre-defined network architectures.

Hardware-Software Integration: Solutions that depend on unified protective strategies such that algorithmic countermeasures presume software design as attack-aware.

Real World Attacks: Moving beyond proof of concept in the lab to real-world attacks on actual off-the-shelf devices with realistic access and trace quality limitations.

Comprehensive Benchmark: A complete, elaborate benchmark for valid evaluation of attack and defense strategies under various implementation and



attack/design thresholds.

The side channel security landscape has been transformed by the advent of deep learning. On the one hand, attacks using neural networks are easy and efficient; on the other hand, they enable ML for detection and trained responses for defense. Because attacks and defenses will always be in a state of flux, side channel security will sustain an expanding line of research. We facilitate future research with our open-source implementation at [github.com/ahmedtaha100/ML\\_Cryptanalyst](https://github.com/ahmedtaha100/ML_Cryptanalyst). Our endeavor—made publicly available to the security community—aims to serve as a one-stop vulnerability test to facilitate the incremental security of any cryptographic implementation with its new findings and potential defenses against other hidden vulnerabilities.

As embedded applications, IoT applications, and even cloud applications continue to rely on such cryptographic implementations more and more, these implementations need to be assessed for vulnerabilities to side channel attacks. This project illustrates how we need to question our prior assumptions of security now that we're in a world dominated by ML, and we need to conduct research which generates new assumptions of security that hold up against what today's neural networks can quickly ascertain.

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The complete implementation of the techniques described in this paper are <sup>499</sup>  
available at [Github.com/AhmedTaha100/ML\\_Cryptanalyst](https://github.com/AhmedTaha100/ML_Cryptanalyst).

1.	<i>This manuscript began as a term project for Johns Hopkins University for course EN.695.641.81.</i>	Paragraph can be improved	Clarity
2.	<i>been expanded</i>	Passive voice misuse	Clarity
3.	<del>traces needed</del> → required traces, traces required	Word choice	Engagement
4.	, and -	Comma misuse within clauses	Correctness
5.	<i>We evaluate convolutional neural networks (CNNs), Long Short Term Memory (LSTM), and Transformers on power traces from side-channel attacks on AES, RSA and ECC.</i>	Paragraph can be improved	Clarity
6.	<del>less</del> → fewer	Misuse of quantifiers	Correctness
7.	<i>Deep learning only needs 80%-90% less traces than differential power analysis.</i>	Paragraph can be improved	Clarity
8.	<i>Second-order masked attempts fall victim to ensemble attacks needing only 3000-5000 traces.</i>	Paragraph can be improved	Clarity
9.	, while	Punctuation in compound/complex sentences	Correctness
10.	<i>Transformers exceed 20-40% better than CNNs while LSTMs level off at 60-75% even though it's off by 1000 samples.</i>	Paragraph can be improved	Clarity
11.	<i>The vulnerabilities we discover include constant-time implementations which leak information due to power variations; Montgomery ladder RSA leaks 60-70% of its exponent bits and even Curve25519 succumbs to transformer attacks.</i>	Ungrammatical sentence	Correctness
12.	a cryptographic	Determiner use (a/an/the/this, etc.)	Correctness

13.	<i>Our open-source implementations show that neural networks can find non-linear mapping patterns and automatically extract features without the need for cryptographic background.</i>	Paragraph can be improved	Clarity
14.	<del>learning-based</del> → learning-based	Misspelled words	Correctness
15.	<i>Our findings show that current defenses do not protect against machine learning based attacks.</i>	Paragraph can be improved	Clarity
16.	<del>Side-channel</del> → Side-channel	Misspelled words	Correctness
17.	<i>Side channel attacks are a sophisticated type of cryptanalysis that target not the calculated, formulaic understanding of an algorithm but information gleaned unintentionally through physical channels while the cryptographic algorithm is running.</i>	Paragraph can be improved	Clarity
18.	<del>side-channel</del> → side-channel	Misspelled words	Correctness
19.	<i>extensive attacker involvement was required</i>	Passive voice misuse	Clarity
20.	<i>be run</i>	Passive voice misuse	Clarity
21.	<i>, and</i>	Punctuation in compound/complex sentences	Correctness
22.	<i>Where before extensive attacker involvement was required to the extent that statistical tests needed to be run to potentially determine a successful attack, now learning the parameters to identify a successful attack is no longer required knowledge and attack success rates have improved significant...</i>	Paragraph can be improved	Clarity

23.	<i>Picek et al. (2023) synthesizes findings from previously published works to document this transformation that deep learning has enabled for physical side channel analysis, allowing researchers to pursue more streamlined yet highly successful attacks.</i>	Ungrammatical sentence	Correctness
24.	<i>Picek et al. (2023) synthesizes findings from previously published works to document this transformation that deep learning has enabled for physical side channel analysis, allowing researchers to pursue more streamlined yet highly successful attacks.</i>	Paragraph can be improved	Clarity
25.	<i>For example, where DPA and CPA required the attacker to know what the algorithm was doing, how the hardware or software operated, AI attacks require basic background knowledge [3] of the target algorithm and collection of power traces from the device to potentially extract secret keys.</i>	Ungrammatical sentence	Correctness
26.	to extract secret keys potentially	Inappropriate colloquialisms	Delivery
27.	<i>For example, where DPA and CPA required the attacker to know what the algorithm was doing, how the hardware or software operated, AI attacks require basic background knowledge [3] of the target algorithm and collection of power traces from the device to potentially extract secret keys.</i>	Paragraph can be improved	Clarity
28.	, and	Comma misuse within clauses	Correctness
29.	<i>This survey examines the advancements, methods of attack and results of AI-based side channel attacks focusing on power analysis attacks against crypto-processing hardware and software.</i>	Paragraph can be improved	Clarity

30.	<i>The concept of power analysis attacks stems from the idea that the power a device expends to calculate information represents the information itself.</i>	Paragraph can be improved	Clarity
31.	<del>different</del> → various	Word choice	Engagement
32.	varying values of data	Word choice	Engagement
33.	<i>This theory is valid because integrated circuits expend different power amounts under different operating conditions and with different data values.</i>	Paragraph can be improved	Clarity
34.	<i>For instance, complementary metal-oxide-semiconductor (CMOS) integrated circuits—which make up almost every computing device produced and utilized today—expend power one way during a charge (changing configurations) and another when static (off).</i>	Paragraph can be improved	Clarity
35.	<i>Further, CMOS integrated circuits expend power to switch states when determining binary 1s and 0s as input data [11].</i>	Paragraph can be improved	Clarity
36.	<del>properly</del> → correctly	Word choice	Engagement
37.	are toggled	Incorrect verb forms	Correctness
38.	<i>Thus, the total power used is directly proportional to how many gates toggled, and the logic is informed directly by what data is processed.</i>	Paragraph can be improved	Clarity
39.	<del>Thus</del> → Therefore, Hence	Word choice	Engagement
40.	<i>In addition, static CMOS power consumption is negligible when high or low states are active; at the same time, there is an incremental power increase when switching states.</i>	Paragraph can be improved	Clarity



41.	<i>Thus, when involving encryption, the power consumption activity factor <math>a</math> becomes data dependent, which attackers can then use to their advantage.</i>	Paragraph can be improved	Clarity
42.	<i>This</i>	Intricate text	Clarity
43.	<i>is called</i>	Passive voice misuse	Clarity
44.	<del>side-channel</del> → side-channel	Misspelled words	Correctness
45.	<i>This is called a side channel vulnerability, which occurs based on leakage modeling expectations.</i>	Paragraph can be improved	Clarity
46.	<del>what occurs</del> → the actual behavior	Paragraph can be improved	Clarity
47.	<del>occurs</del> → happens, appears	Word choice	Engagement
48.	<i>is purely expected</i>	Passive voice misuse	Clarity
49.	<i>The Hamming Weight model indicates that power is drawn based on how many bits in the value are equal to one.</i>	Paragraph can be improved	Clarity
50.	than 1	Wrong or missing prepositions	Correctness
51.		Tone suggestions	Delivery
52.	<i>This models reality somewhat because it's true that manipulating a value with more 1 bits is going to probably require more signal toggling in the combinational logic needed to generate it, but it's a theory based on observation.</i>	Paragraph can be improved	Clarity
53.	<i>is based</i>	Passive voice misuse	Clarity
54.	<i>The Hamming Distance model indicates that power consumed is based on how many bit transitions occur.</i>	Paragraph can be improved	Clarity

55.	<del>models</del> → <del>model</del>	Incorrect noun number	Correctness
56.	<i>are made</i>	Passive voice misuse	Clarity
57.		Tone suggestions	Delivery
58.	<i>This models reality a little better because it applies directly to how many transitions are made when using dynamic power and the sequential logic required to switch registers from value x to value y.</i>	Paragraph can be improved	Clarity
59.	<i>Therefore, these are all models of leakage that are analogous to what one might find in the real world; however, they do not account for all leakage.</i>	Paragraph can be improved	Clarity
60.	<del>ertain</del> → <del>specific</del>	Word choice	Engagement
61.	<i>For example, with integrated circuits, there could be leakage based on some bits more than others (certain bit positions leak worse than others) or value-dependent leakage (certain data values give a different signature of power).</i>	Paragraph can be improved	Clarity
62.	<i>Either way, the best method to determine which type of leakage model applies to one's situation is through real testing on the actual targeted device [4].</i>	Paragraph can be improved	Clarity
63.	<i>In addition to hardware side channel attacks with considered leakage, much is at stake for assessment of side channel attacks as well.</i>	Ungrammatical sentence	Correctness
64.	<i>The Nyquist-Shannon theorem states that sampling must occur at greater than double the highest frequency of interest [13].</i>	Paragraph can be improved	Clarity
65.	<del>ertain</del> → <del>specific</del>	Word choice	Engagement
66.	<del>a certain</del>	Determiner use (a/an/the/this, etc.)	Correctness

67.	to obtain all power characteristics accurately	Inappropriate colloquialisms	Delivery
68.	<del>side-channel</del> → side-channel	Misspelled words	Correctness
69.	<i>Yet many side channel attacks find success with much lower sampling frequencies, such as 1 GS/s [2].</i>	Paragraph can be improved	Clarity
70.	<del>where</del> → Where -	Improper formatting	Correctness
71.	signal-dependent	Misspelled words	Correctness
72.	<i>In a controlled environment with access to sophisticated oscilloscopes, shielding, and stable triggering, one is able to obtain SNR values greater than 20 dB for the unprotected measurements [15].</i>	Paragraph can be improved	Clarity
73.	countermeasures; countermeasure; Countermeasures; Counter-Measures	Text inconsistencies	Correctness
74.	<i>For the protected measurements where countermeasures take place, the SNR may be negative for the leakage of interest, which means more extensive statistical testing is required.</i>	Paragraph can be improved	Clarity
75.	be measured	Passive voice misuse	Clarity
76.	drops,	Punctuation in compound/complex sentences	Correctness
77.	<i>That is, which samples/times demonstrate leakage?</i>	Paragraph can be improved	Clarity
78.	<i>For example, when an implementation has no protection, the POI will coincide with when vulnerable intermediate values are read/written.</i>	Paragraph can be improved	Clarity
79.	<del>a number of</del> → several	Paragraph can be improved	Clarity

80.	<del>he or she sees</del> → <b>they see</b>	Potentially sensitive language	Delivery
81.	<i>For instance, Simple Power Analysis (SPA) has an attacker simply looking at power traces and determining what has happened based on what he or she sees along the way.</i>	Paragraph can be improved	Clarity
82.		Tone suggestions	Delivery
83.	<i>Differential Power Analysis (DPA) is somewhat similar because it too relies upon power consumption and vulnerabilities generated from such analysis; however, this time, the attacker must correlate consumption with the likeliest values generated from set keys.</i>	Paragraph can be improved	Clarity
84.	<i>The attacker takes a key guess and computes what intermediate values would yield during execution—computes power consumption—and repeats for each successive key guess, enabling them to determine which hypothesis has the highest correlation with consumed power.</i>	Paragraph can be improved	Clarity
85.	<b>, but</b>	Punctuation in compound/complex sentences	Correctness
86.	<i>DPA does not require implementation awareness but instead of a single trace, it needs thousands [11].</i>	Paragraph can be improved	Clarity
87.	<i>Correlation Power Analysis (CPA) is essentially DPA but with the Pearson correlation coefficient.</i>	Paragraph can be improved	Clarity
88.	<i>It measures how well the predicted power and measured power correlate with each other.</i>	Paragraph can be improved	Clarity
89.	<del>predict</del> → <b>indicate</b>	Word choice	Engagement

90.	<i>CPA does this in a transparent fashion by using a leakage model like HW or HD to predict the amount of power used.</i>	Paragraph can be improved	Clarity
91.	<i>So, if a leakage model holds true for the device under attack, then CPA is better than DPA [6].</i>	Paragraph can be improved	Clarity
92.	<del>true</del>	Wordy sentences	Clarity
93.	<i>This</i>	Intricate text	Clarity
94.	<i>, which</i>	Punctuation in compound/complex sentences	Correctness
95.	<del>own</del>	Wordy sentences	Clarity
96.	<i>This attack can use pooled covariance matrices across the templates so as to lessen the profiler's need for access.</i>	Paragraph can be improved	Clarity
97.	<i>This</i>	Intricate text	Clarity
98.	<i>in place.</i>	Paragraph can be improved	Clarity
99.	<i>, including</i>	Punctuation in compound/complex sentences	Correctness
100.	<i>However, contemporary cryptographic devices employ countermeasures including masking (splitting critical variables into random shares), shuffling (randomization of operation order), and hiding (noise or dummy operations) that make these attacks significantly more difficult.</i>	Paragraph can be improved	Clarity
101.	<i>For instance, these countermeasures can cause SNRs to become negative and demand higher-order assessment or more complicated approaches, which are the basis for the machine learning techniques assessed in later sections.</i>	Paragraph can be improved	Clarity

102.	, and	Comma misuse within clauses	Correctness
103.	<i>This subsection describes the threat model for the side channel attacks studied in this research, what the attacker can (and cannot) do and under what attack parameters.</i>	Paragraph can be improved	Clarity
104.	the effective, or an effective	Determiner use (a/an/the/this, etc.)	Correctness
105.	<i>There is no virtual/remote operation.</i>	Paragraph can be improved	Clarity
106.	<i>is decapsulated</i>	Passive voice misuse	Clarity
107.	<i>is opened</i>	Passive voice misuse	Clarity
108.	<i>A semi-invasive attack—where a chip is decapsulated although no interference occurs with the circuitry now visible when the chip is opened—is associated with other research.</i>	Paragraph can be improved	Clarity
109.	<del>common</del> → standard	Word choice	Engagement
110.	<del>side-channel</del> → side-channel	Misspelled words	Correctness
111.	<i>The models evaluated in our work, for instance, operate on GPUs with at least 8GB memory and require hours or days to train depending on the architecture complexity and the size of the training and testing dataset.</i>	Paragraph can be improved	Clarity
112.	<del>if</del> → If	Improper formatting	Correctness
113.	<del>gpue</del> → GPUs	Misspelled words	Correctness
114.	<del>memoryUsed</del> → memory used	Misspelled words	Correctness
115.	- or software-based	Paragraph can be improved	Clarity
116.	<del>software-based</del> → software-based	Misspelled words	Correctness

117.	<i>For profiled attacks, the attacker possesses the targeted device or a similar one and has control over the input during profiling.</i>	Paragraph can be improved	Clarity
118.	<del>victim</del> → victim's	Incorrect noun number	Correctness
119.	<i>This</i>	Intricate text	Clarity
120.	typically, -	Punctuation in compound/complex sentences	Correctness
121.	<del>in excess of</del> → more than, over	Wordy sentences	Clarity
122.	<del>important</del> → significant	Word choice	Engagement
123.	Several important limitations restrict	Wordy sentences	Clarity
124.	<i>The attacker cannot have invasive access, meaning no internal circuit manipulation, no fault injection, nor operational changes to the device.</i>	Ungrammatical sentence	Correctness
125.	<del>victim</del> → victim's	Incorrect noun number	Correctness
126.	<i>In some cases, the attack collection window is limited (for instance, a payment card attack can happen in seconds while the card is engaged).</i>	Paragraph can be improved	Clarity
127.	<del>side-channel</del> → side-channel	Misspelled words	Correctness
128.	<i>The attacker has no access to key storage/key generation aside from side channel leakage.</i>	Paragraph can be improved	Clarity
129.	, which	Punctuation in compound/complex sentences	Correctness
130.	being done	Passive voice misuse	Clarity

131.	<i>Operational conditions are that the attacked device works under nominal conditions—voltage standard <math>\pm 10\%</math> and temperature 0-70 degrees C.</i>	Paragraph can be improved	Clarity
132.	the operation	Determiner use (a/an/the/this, etc.)	Correctness
133.	<i>There is a reliable clock source; jitter occurs under 1% of the clock period, and operation is repeatable so that the same operation produces statistically similar traces.</i>	Paragraph can be improved	Clarity
134.	The sampling	Determiner use (a/an/the/this, etc.)	Correctness
135.	<i>The following are the measurement conditions: Sampling rate is at least 5× the anticipated clock frequency for power analysis.</i>	Paragraph can be improved	Clarity
136.	<del>2x</del> → 2 times the	Paragraph can be improved	Clarity
137.	, with	Punctuation in compound/complex sentences	Correctness
138.	The signal-to-noise	Determiner use (a/an/the/this, etc.)	Correctness
139.	<i>masking countermeasures should be applied</i>	Passive voice misuse	Clarity
140.	<i>is drawn</i>	Passive voice misuse	Clarity
141.	prior to certification	Paragraph can be improved	Clarity
142.	, and	Punctuation in compound/complex sentences	Correctness



143.	<i>Finally, certification assessment occurs when a third-party assessment laboratory assesses the device against Common Criteria or FIPS 140-3 requirements either as a standardized test vector.</i>	Paragraph can be improved	Clarity
144.	<del>having</del>	Incorrect verb forms	Correctness
145.	<del>, not</del>	Punctuation in compound/complex sentences	Correctness
146.	<i>what's provided</i>	Passive voice misuse	Clarity
147.	<i>Field attacks represent the final deployment, meaning attackers only have limited access for a limited amount of time in a noncontrolled environment having not much more profiling than what's provided during final deployment.</i>	Paragraph can be improved	Clarity
148.	<i>Supply chain attacks mean that attackers have access but only for as long as packaging or shipping, which means they are more likely to profile their attack sample based on the samples received during production.</i>	Paragraph can be improved	Clarity
149.	<del>means</del> → indicates	Word choice	Engagement
150.	<i>Remote power analysis means that attackers can perform attacks based on unintentional electromagnetic emanation that is perceivable at a distance or based on power consumption activities observable in shared power supply systems.</i>	Paragraph can be improved	Clarity
151.	<del>and does</del> → . It does	Hard-to-read text	Clarity
152.	<del>side-channel</del> → side-channel	Misspelled words	Correctness
153.	<i>Other evaluations would be necessary for more robust attackers with invasive access or more minimal attackers operating remotely.</i>	Paragraph can be improved	Clarity

154.	<del>Side Channel</del> → Side-Channel	Misspelled words	Correctness
155.	<del>side channel</del> → side-channel	Misspelled words	Correctness
156.	<i>Machine learning transforms side channel attacks from complex exploits requiring unique expertise to automated attack processes.</i>	Paragraph can be improved	Clarity
157.	<i>Machine learning transforms side channel attacks through two main approaches: profiled attacks using identical devices for training, and non-profiled attacks that learn directly from the target.</i>	Ungrammatical sentence	Correctness
158.	<i>Machine learning transforms side channel attacks through two main approaches: profiled attacks using identical devices for training, and non-profiled attacks that learn directly from the target.</i>	Paragraph can be improved	Clarity
159.	<i>The first is a profiled attack, meaning that the attacker has the same or a similar device to train on.</i>	Paragraph can be improved	Clarity
160.	<i>The profiling phase entails gathering power traces from the profiling device while it engages in cryptographic activity with known keys; this process creates labeled datasets that allow machine learning models to understand the classification of power patterns to specific key values or intermediate...</i>	Paragraph can be improved	Clarity
161.	<i>This</i>	Intricate text	Clarity
162.	<i>ndarray</i>	Unknown words	Correctness
163.	<i>ndarray</i>	Unknown words	Correctness
164.	<i>""""</i>	Comma misuse within clauses	Correctness
165.	<del>victim</del> → victim's	Incorrect noun number	Correctness

166.	<i>Non-profiled attacks bring the assault directly to the victim device, implying that it attacks a device without ever being trained on the same device beforehand.</i>	Paragraph can be improved	Clarity
167.	<i>This</i>	Intricate text	Clarity
168.	<i>This</i>	Intricate text	Clarity
169.	<del>obviously</del> -	Wordy sentences	Clarity
170.	<del>create</del> → develop	Word choice	Engagement
171.	<i>This obviously creates a much more complicated scenario, albeit a much more realistic one, should a malicious entity not be able to create a profiling device.</i>	Paragraph can be improved	Clarity
172.	learning-oriented	Misspelled words	Correctness
173.	<i>Ultimately, the attack's machine learning oriented approach has the same logic to create a linear pipeline.</i>	Paragraph can be improved	Clarity
174.	<del>side-channel</del> → side-channel	Misspelled words	Correctness
175.	<i>For example, for data collection, power traces are recorded via oscilloscopes or dedicated side channel acquisition devices where data collection occurs from power traces garnered in side channel attacks.</i>	Paragraph can be improved	Clarity
176.	<i>is generated</i>	Passive voice misuse	Clarity
177.	a single side-channel	Paragraph can be improved	Clarity
178.	<i>Therefore, for memory efficiency versus a slight loss of accuracy, power traces are stored in float32 arrays.</i>	Paragraph can be improved	Clarity
179.	variance,	Punctuation in compound/complex sentences	Correctness

180.	<i>Features are standardized to achieve a mean of zero and unit variance, or normalized into [0,1] or [-1,1].</i>	Paragraph can be improved	Clarity
181.	<i>is adjusted</i>	Passive voice misuse	Clarity
182.	<i>High-frequency noise or 50/60Hz noise gets filtered out.</i>	Paragraph can be improved	Clarity
183.	<del>occure via</del> → is achieved through	Paragraph can be improved	Clarity
184.	<i>ndarray</i>	Unknown words	Correctness
185.	<i>ndarray</i>	Unknown words	Correctness
186.	<del>""</del>	Comma misuse within clauses	Correctness
187.	<del>" Align</del>	Improper formatting	Correctness
188.	<del>if</del> → If	Improper formatting	Correctness
189.	<i>Feature extraction happens where points of interest occur within the cleaned traces that denote moments of leakage.</i>	Paragraph can be improved	Clarity
190.	<i>are learned</i>	Passive voice misuse	Clarity
191.	<i>ndarray</i>	Unknown words	Correctness
192.	<i>ndarray</i>	Unknown words	Correctness
193.	<i>ndarray</i>	Unknown words	Correctness
194.	<del>""</del>	Comma misuse within clauses	Correctness
195.	<i>For profiled attacks, this means supervised training with a device under attack correlating power traces with its generated key bytes.</i>	Paragraph can be improved	Clarity
196.	<i>are based</i>	Passive voice misuse	Clarity

197.	<del>upon</del> → on	Wrong or missing prepositions	Correctness
198.	<i>For non-profiled attacks, unsupervised learning applies clustering techniques to identify predicted traces that are based upon the use of keys.</i>	Paragraph can be improved	Clarity
199.	<i>The problem of class imbalance poses issues when some predicted key values are more likely than others, but solutions exist through balanced sampling and weighted loss functions to ensure a more even output during training operations.</i>	Paragraph can be improved	Clarity
200.	<i>is tested</i>	Passive voice misuse	Clarity
201.	<i>been trained</i>	Passive voice misuse	Clarity
202.	<i>what's expected</i>	Passive voice misuse	Clarity
203.	<i>The model assesses what's been trained and what's expected, outputting a probability distribution of expected key values for each byte.</i>	Paragraph can be improved	Clarity
204.	a more	Determiner use (a/an/the/this, etc.)	Correctness
205.	<i>is required</i>	Passive voice misuse	Clarity
206.	<i>Deep learning approaches have better key recovery in comparison to traditional statistical methods [2, 4].</i>	Paragraph can be improved	Clarity
207.	<i>are selected</i>	Passive voice misuse	Clarity
208.	<del>properly</del> → correctly	Word choice	Engagement

209.	<i>With a neural network, the most appropriate features are selected automatically, and they function properly with complicated leakage types (higher order effects, masked implementations).</i>	Paragraph can be improved	Clarity
210.	<del>is</del> → are	Faulty subject-verb agreement	Correctness
211.	<i>In addition, overfitting is always a problem since the number of trace features is greater than the number of observations, so regularization and early stopping based on key recovery metrics (not validation loss) is essential.</i>	Paragraph can be improved	Clarity
212.	Many neural network architectures have	Wordy sentences	Clarity
213.	<del>side channel</del> → side-channel	Misspelled words	Correctness
214.	<del>certain</del> → specific	Word choice	Engagement
215.	<i>There are many neural network architectures that have been successful for side channel analysis, providing certain advantages for different attack scenarios.</i>	Paragraph can be improved	Clarity
216.	<i>These include an adjusted success rate based on attack type, similar to Hettwer and Güneysu (2020)'s extensive survey.</i>	Ungrammatical sentence	Correctness
217.	<i>Therefore, solutions of a more recent vintage use ensemble methods and transfer learning as well, either blending the subsequent architectures or using the learned models from one implementation to attack a similarly trained implementation based on only a handful of trained samples.</i>	Paragraph can be improved	Clarity
218.	<del>side channel</del> → side-channel	Misspelled words	Correctness

219.	<i>One of the most powerful architectures applied to side channel attacks is CNN, which is capable of evaluating spatial features from power traces with little to no pretreatment of the data.</i>	Paragraph can be improved	Clarity
220.	...	Misuse of semicolons, quotation marks, etc.	Correctness
221.	<del>side-channel</del> → <i>side-channel</i>	Misspelled words	Correctness
222.	<i>are required</i>	Passive voice misuse	Clarity
223.	<i>Moreover, kernel sizes are large, 11 or greater, to identify long-range dependencies in power traces as opposed to small kernels in imaging; some kernels are size 21 or 31.</i>	Paragraph can be improved	Clarity
224.	<i>be discarded</i>	Passive voice misuse	Clarity
225.	<i>Max pooling is avoided in favor of average pooling as average pooling maintains magnitude information—low amplitude leakage information should not be discarded, but average pooling can retain such low values.</i>	Paragraph can be improved	Clarity
226.	<del>important</del> → <i>essential, vital</i>	Word choice	Engagement
227.	<i>This</i>	Intricate text	Clarity
228.	<i>example,</i>	Comma misuse within clauses	Correctness
229.	<del>greatest</del> → <i>most significant, most tremendous</i>	Word choice	Engagement
230.	<i>LSTMs maintain an internal state across time steps, allowing them to determine the association between two operations even when they appear in time-disjointed, yet temporally connected, sequences.</i>	Ungrammatical sentence	Correctness

231.	<del>information</del> → data	Word choice	Engagement
232.	that represents	Pronoun use	Correctness
233.	<i>Another method includes implementing a Bidirectional LSTM to process the power trace in time-disjointed, yet aligned, sequences as well.</i>	Ungrammatical sentence	Correctness
234.	<i>This</i> -	Intricate text	Clarity
235.	<i>be lost</i>	Passive voice misuse	Clarity
236.	<i>For example, when leakage from an operation that occurs after the viewed operation relies on an earlier read, such a technique helps.</i>	Paragraph can be improved	Clarity
237.	<i>Using power coupling or electromagnetic radiation, for example, might obscure the first operation's detection due to the time delay in arrival of information relating to the operation that came first but rendered later.</i>	Ungrammatical sentence	Correctness
238.	<i>Using power coupling or electromagnetic radiation, for example, might obscure the first operation's detection due to the time delay in arrival of information relating to the operation that came first but rendered later.</i>	Paragraph can be improved	Clarity
239.	<i>These networks are a merger between CNN feature extraction and LSTM temporal processing, thus holding the benefits of both worlds.</i>	Paragraph can be improved	Clarity
240.	<del>in relation to</del> → about, to, with, concerning	Wordy sentences	Clarity
241.	, and	Punctuation in compound/complex sentences	Correctness
242.	<i>is observed</i>	Passive voice misuse	Clarity



243.	<i>Since CNN layers focus on local features, and LSTM layers deal with what features change over time in relation to the operations conducted during the cryptographic process, such an architecture works best when protected implementations are under attack and time-dependent leakage is observed over va...</i>	Paragraph can be improved	Clarity
244.	<i>The latest breakthrough in deep learning for side channel attacks has come from Transformers, which use a self-attention mechanism to process an entire trace all at once rather than sequentially.</i>	Ungrammatical sentence	Correctness
245.	<i>The latest breakthrough in deep learning for side channel attacks has come from Transformers, which use a self-attention mechanism to process an entire trace all at once rather than sequentially.</i>	Paragraph can be improved	Clarity
246.	<i>. Then it generates</i>	Hard-to-read text	Clarity
247.	<i><del>that can</del> → and can</i>	Conjunction use	Correctness
248.	<i>Therefore, the global receptive field exceeds that of CNNs and RNNs that can only learn features in a local input field or sequentially.</i>	Paragraph can be improved	Clarity
249.	<i>In addition, note that attention weights are visible for interpretability as researchers can see which segment of the trained trace was most responsible for successfully retrieving a specific key; this is opposite to CNN and LSTM designs from which no human interpretability is possible.</i>	Paragraph can be improved	Clarity
250.	<i><del>side-channel</del> → side-channel</i>	Misspelled words	Correctness
251.	<i>In 2024, Bursztein et al. introduced GPAM (Generalized Power Analysis Model), a Transformer-based architecture that represents a significant advancement in automated side channel attacks.</i>	Paragraph can be improved	Clarity

252.	, including	Punctuation in compound/complex sentences	Correctness
253.	<del>side-channel</del> → side-channel	Misspelled words	Correctness
254.	<i>The proposed CNN architecture has <math>O(L \cdot k \cdot n \cdot d^2)</math> computational complexity where <math>L</math>=number of layers, <math>k</math>=kernel size, <math>n</math>=sequence length, and <math>d</math>=number of filters, with parallelizability of operations.</i>	Paragraph can be improved	Clarity
255.	<i>must be done</i>	Passive voice misuse	Clarity
256.	, therefore	Punctuation in compound/complex sentences	Correctness
257.	<i>The proposed RNN and LSTM have <math>O(n \cdot d^2)</math> complexity with sequential operations that must be done in order and therefore, not parallelizable.</i>	Paragraph can be improved	Clarity
258.	<i>The Transformer architecture has <math>O(n^2 \cdot d)</math> memory complexity where <math>n</math>=sequence length and <math>d</math>=model dimension, with parallelization occurring.</i>	Paragraph can be improved	Clarity
259.	<i>The limit to the GPU memory factoring for the transformation architecture lends itself to traces no larger than 50,000 samples, needing to square the memory used.</i>	Paragraph can be improved	Clarity
260.	<i>was achieved</i>	Passive voice misuse	Clarity
261.	<i>was obtained</i>	Passive voice misuse	Clarity
262.	<i>Finally, the approach of transfer learning lessens the necessity to profile all traces where one trained on one device's implementation was transferable on a similar implementation using the already trained model with minimal profiling needed.</i>	Paragraph can be improved	Clarity
263.	<del>side-channel</del> → side-channel	Misspelled words	Correctness

264.	<i>Power trace preprocessing and feature extraction are crucial for the success of ML-based side channel attacks.</i>	Paragraph can be improved	Clarity
265.	<i>Power traces are extremely noisy with anywhere between 10,000 to 1,000,000 samples per encrypt/decrypt operation, making alignment and denoising as well as extracting useful features critical before any neural network processing can take place.</i>	Ungrammatical sentence	Correctness
266.	<i>Power traces are extremely noisy with anywhere between 10,000 to 1,000,000 samples per encrypt/decrypt operation, making alignment and denoising as well as extracting useful features critical before any neural network processing can take place.</i>	Paragraph can be improved	Clarity
267.	<i>Time complexity for such processing is dependent upon which processing algorithms are used.</i>	Paragraph can be improved	Clarity
268.	The time	Determiner use (a/an/the/this, etc.)	Correctness
269.	are used	Passive voice misuse	Clarity
270.	, if performed via FFT acceleration, where $n$ is the length of the trace and $m$ ,	Comma misuse within clauses	Correctness
271.	, plus	Punctuation in compound/complex sentences	Correctness
272.	<i>If the dataset is too large, memory-mapped files are needed for streaming processing to avoid memory use in RAM.</i>	Paragraph can be improved	Clarity
273.	is removed	Passive voice misuse	Clarity

274.	<i>For example, DC offset is removed, which represents constant additions from measuring tools that corrupt raw measurements usually in the millivolt range to volts from various power testing tools and configurations.</i>	Ungrammatical sentence	Correctness
275.	<i>For example, DC offset is removed, which represents constant additions from measuring tools that corrupt raw measurements usually in the millivolt range to volts from various power testing tools and configurations.</i>	Paragraph can be improved	Clarity
276.	<i>Detrending removes linear/polynomial additions that happen over time either through temperature drift (deviating 0.1-1% per Celsius) or power supply adjustments.</i>	Paragraph can be improved	Clarity
277.	<i>Filtering removes the high-frequency noises yet keeps the cryptographic leakage, with low cut-off frequencies typically between 0.1 to 0.5 of the clock device frequency running.</i>	Paragraph can be improved	Clarity
278.	<i>;</i> → <i>;</i>	Misuse of semicolons, quotation marks, etc.	Correctness
279.	<i>;</i> → <i>;</i>	Misuse of semicolons, quotation marks, etc.	Correctness
280.	<i>;</i> → <i>;</i>	Misuse of semicolons, quotation marks, etc.	Correctness
281.	<i>;</i> → <i>;</i>	Misuse of semicolons, quotation marks, etc.	Correctness
282.	<del>for</del> → For	Improper formatting	Correctness
283.	the pipeline	Determiner use (a/an/the/this, etc.)	Correctness
284.	be performed	Passive voice misuse	Clarity

285.	<i>Point Of Interest (POI) Selection occurs when researchers know which samples in the power traces will be most beneficial, meaning that fewer calculations need to be performed and successful attack percentages increase.</i>	Paragraph can be improved	Clarity
286.	<i>The Sum of Squared T-statistics (SOST) is used to determine which points the power consumption varies the greatest for the different key hypotheses, meaning that it exhibits high leakage.</i>	Paragraph can be improved	Clarity
287.	<i>It calculates class means for each key hypothesis and looks at the variance between class means compared to the weighted means of the sizes of each class.</i>	Paragraph can be improved	Clarity
288.	<i>is transmitted</i>	Passive voice misuse	Clarity
289.	<i>information-theoretic</i>	Misspelled words	Correctness
290.	<i>It captures linear and non-linear relationships, and therefore, this information theoretic method may reveal leakages that a simple correlation-based assessment would not.</i>	Paragraph can be improved	Clarity
291.	<i>Incremental PCA allows for data to be processed in batches as well, meaning that even a dataset larger than the current RAM can get processed.</i>	Paragraph can be improved	Clarity
292.	<i>The number of components can be selected</i>	Passive voice misuse	Clarity
293.	<i>The number of components can be selected to retain a specific amount of variance after trimming, ideally 95-99% for any reduction in side channel detection.</i>	Paragraph can be improved	Clarity
294.	<i><del>important</del> → essential</i>	Word choice	Engagement

295.	<i>Data augmentation provides the illusion of additional data points and can improve the generalizability of the model, which is important when limited experimental profiling traces exist.</i>	Paragraph can be improved	Clarity
296.	<i>Adding Gaussian noise with amplitude 5-10% of the trace's standard deviation improves model generalization.</i>	Ungrammatical sentence	Correctness
297.	<i>Random shifting teaches the models to learn from misaligned shifts where no alignment is guaranteed, generally trained at <math>\pm 50</math>-100 samples.</i>	Paragraph can be improved	Clarity
298.	<del>important</del> → essential, vital	Word choice	Engagement
299.	<del>same</del> → exact	Word choice	Engagement
300.	<i>Amplitude scaling is important to integrate gain differences from the same measurement taken on different days, usually differing from 0.9-1.1.</i>	Paragraph can be improved	Clarity
301.	<del>provided</del> → provides	Incorrect verb forms	Correctness
302.	<i>The noise is adjusted to maintain a realistic signal-to-noise ratio but provided enough variance to train effectively without overfitting.</i>	Paragraph can be improved	Clarity
303.	<del>filepath</del> → file path	Misspelled words	Correctness
304.	<del>filepath</del> → file path	Misspelled words	Correctness
305.	the generalization	Determiner use (a/an/the/this, etc.)	Correctness
306.	<i>The effective dimensionality increases from 2-10× due to data augmentation, which helps generalization of the model, particularly for obfuscated implementations.</i>	Paragraph can be improved	Clarity

307.	<i>Processing speeds on modern devices range from 1,000-10,000 traces per second, depending on whether or not preprocessing is required and how long that preprocessing takes.</i>	Paragraph can be improved	Clarity
308.	<del>channel-based</del> → channel-based	Misspelled words	Correctness
309.	<i>Widespread, popular cryptographic implementations have vulnerabilities exploited by deep learning side channel based attacks.</i>	Paragraph can be improved	Clarity
310.	learning-founded	Misspelled words	Correctness
311.	<i>The shift in the area of attack from traditional, statistical, resource-heavy investigation to trained, predictable, deep learning founded projections suggests easier, more efficient penetrations are on the rise.</i>	Paragraph can be improved	Clarity
312.	<i>AES implementations are susceptible to such things as well.</i>	Paragraph can be improved	Clarity
313.	assessment,	Punctuation in compound/complex sentences	Correctness
314.	<i>For example, an authenticating neural network-based power analysis attack reveals higher accuracy in its software implementations via SubBytes assessment where the non-linearity of S-box during SubBytes creates a distinguishable power consumption profile.</i>	Paragraph can be improved	Clarity
315.	<i>Therefore, CNNs trained—especially with larger convolution kernels—find these patterns faster (50-to-100 traces for attacking unprotected SubBytes implementations as opposed to hundreds with traditional investigations) [2].</i>	Paragraph can be improved	Clarity

316.	<i>Yet even first-order masked AES implementations in the ASCAD database are susceptible to sophisticated ML attacks.</i>	Paragraph can be improved	Clarity
317.	<del>major</del> → significant	Word choice	Engagement
318.	<del>upon</del> → on	Wrong or missing prepositions	Correctness
319.	<i>In a like manner, constant-time implementations rely upon the ability to eliminate timing side channels that even the traces resulting in a live implementation will not stand as an attack vector.</i>	Paragraph can be improved	Clarity
320.	so that	Conjunction use	Correctness
321.	, and	Comma misuse within clauses	Correctness
322.	<i>This occurrence is because, even under constant time, through the physical properties of the CMOS circuit, the Hamming weights of various data values will consume different levels of power.</i>	Paragraph can be improved	Clarity
323.	are reproduced	Passive voice misuse	Clarity
324.	<del>own</del>	Wordy sentences	Clarity
325.	<del>for</del> → For	Improper formatting	Correctness
326.	, while	Punctuation in compound/complex sentences	Correctness
327.	the power	Determiner use (a/an/the/this, etc.)	Correctness
328.	<i>The square-and-multiply technique, even with hardening attempted across the board, still gives away information based on power draw that an ANN categorizes upon.</i>	Paragraph can be improved	Clarity
329.	key.	Closing punctuation	Correctness



330.	<i>are reproduced</i>	Passive voice misuse	Clarity
331.	<del>own</del>	Wordy sentences	Clarity
332.	<i>ndarray</i>	Unknown words	Correctness
333.	<del>key space</del> → <i>keyspace</i>	Confused words	Correctness
334.	<i>The multiplication function called the Montgomery ladder seeks to give the same number of operations regardless of which bits are in an exponent; however, transitions between operators still show minimal differences in power draw that machine learning can find.</i>	Paragraph can be improved	Clarity
335.	<i>Using Chinese Remainder Theorem (CRT) shortcuts to accelerate RSA exposes weaknesses as well.</i>	Paragraph can be improved	Clarity
336.	<i>Being able to perform partial exponentiations in parallel creates distinguishable power signatures that a neural network can separate and learn/analyze.</i>	Paragraph can be improved	Clarity
337.	<del>learn</del> → <i>understand, know</i>	Word choice	Engagement
338.	<del>own</del>	Wordy sentences	Clarity
339.	<del>side channel</del> → <i>side-channel</i>	Misspelled words	Correctness
340.	<i>They have their own vulnerabilities relative to ML-based side channel attacks.</i>	Paragraph can be improved	Clarity
341.	<del>upon</del> → <i>on</i>	Wrong or missing prepositions	Correctness
342.	<i>being multiplied</i>	Passive voice misuse	Clarity
343.	<i>ndarray</i>	Unknown words	Correctness
344.	<del>side channel</del> → <i>side-channel</i>	Misspelled words	Correctness

345.	<i>Our contribution also includes specific attacks against Curve25519 and demonstrates that even this curve, designed to mitigate side channel attacks, still has vulnerabilities.</i>	Paragraph can be improved	Clarity
346.	<i>For example, we show with our lattice attack implementation that after performing an ML-based nonce bit extraction via a power analysis to distinguish the nonce bits, obtaining 4-8 bits per nonce after power analysis over 200-500 signatures can lead to private key recovery in specific scenarios.</i>	Paragraph can be improved	Clarity
347.	<code>ndarray</code>	Unknown words	Correctness
348.	<code>""</code>	Comma misuse within clauses	Correctness
349.	<code>" Lattice</code>	Improper formatting	Correctness
350.	<code>""</code>	Comma misuse within clauses	Correctness
351.	<i>This representation was used</i>	Passive voice misuse	Clarity
352.	<del>are able to</del> → <code>can</code>	Wordy sentences	Clarity
353.	<del>greatly</del> → <code>significantly</code>	Word choice	Engagement
354.	<del>jitter,</del>	Comma misuse within clauses	Correctness
355.	<i>Real-world applications must deal with electromagnetic noise from other devices, temperature fluctuations masking the baseline of power consumption, physical shielding and casings absorbing emanations, and live compensating activities not present on experimental boards.</i>	Paragraph can be improved	Clarity
356.	<i>Furthermore, legitimate devices use many of these at the same time, so the compounding effect lowers these success rates far below what individual countermeasure evaluation would suggest.</i>	Paragraph can be improved	Clarity

357.	<del>side-channel</del> → side-channel	Misspelled words	Correctness
358.	<i>Convolutional Neural Networks demonstrate strong performance for general-purpose side channel analysis, particularly when attacking implementations with localized leakage.</i>	Paragraph can be improved	Clarity
359.	<i>Our experiments show that optimized CNN architectures can achieve 70-85% success rates against first-order masked AES implementations using 1000-2000 traces, representing a 2-5x reduction compared to traditional CPA methods.</i>	Paragraph can be improved	Clarity
360.	<del>max-pooling</del> → max-pooling	Misspelled words	Correctness
361.	<i>This</i>	Intricate text	Clarity
362.	<i>the advantages of spatial detection through the CNN can be utilized</i>	Passive voice misuse	Clarity
363.	<i>Here, the advantages of spatial detection through the CNN can be utilized with time detection from the LSTMs.</i>	Paragraph can be improved	Clarity
364.	<i>For instance, in my research, CNNs hybridized with LSTMs reduce the number of required traces by 15-25% compared to standard CNNs when attacking protected implementations where the leakage happens over multiple timesteps as opposed to one.</i>	Paragraph can be improved	Clarity
365.	<del>for</del>	Wrong or missing prepositions	Correctness
366.	<i>The self-attention mechanism allows for transformers to assess the entire trace at once, determining if two points are correlated no matter how far apart they are in the overall sequence.</i>	Paragraph can be improved	Clarity

367.	<i>We develop a GPAM-type architecture based on transformers and achieve a success rate between 20-40% higher than that of CNNs tested on the same datasets, though at significantly higher computational cost.</i>	Paragraph can be improved	Clarity
368.	<b>focus,</b>	Punctuation in compound/complex sentences	Correctness
369.	<i>The attention heads per layer function at different temporal resolutions; therefore, they learn to pay attention over time to short-term vs. long-term, localized patterns of focus, and macro-level focus of the entire trace.</i>	Paragraph can be improved	Clarity
370.	<del>always</del> → consistently	Word choice	Engagement
371.	<i>Furthermore, ensemble techniques that aggregate different architectures always outperform individual models since they can make up for each other's strengths.</i>	Paragraph can be improved	Clarity
372.	<i>The ensemble works best against second-order masked implementations where an attack can be successfully mounted with decent conditions for 3000-5000 traces by different trained architectural views of the same power consumption.</i>	Paragraph can be improved	Clarity
373.	<b>modeling,</b>	Comma misuse within clauses	Correctness
374.	<del>side-channel</del> → side-channel	Misspelled words	Correctness
375.	<i>A formal quantitative assessment is necessary to evaluate the effectiveness of these ML-based side channel attacks.</i>	Paragraph can be improved	Clarity
376.	<i>Our implementation provides all metrics needed for baseline and relative modifications between attacks and defenses.</i>	Paragraph can be improved	Clarity

377.	<i>Entropy; entropy</i>	Text inconsistencies	Correctness
378.	<i>is generated</i>	Passive voice misuse	Clarity
379.	<i>is attributed</i>	Passive voice misuse	Clarity
380.	log probabilities	Confused words	Correctness
381.	argsort	Unknown words	Correctness
382.	<del>5-20x</del> → 5-20	Misspelled words	Correctness
383.	<del>first order</del> → first-order	Misspelled words	Correctness
384.	<i>The success rate is the probability of guessing the key correctly within x guesses, determined predominantly by first order success (the key in the first spot).</i>	Paragraph can be improved	Clarity
385.	argsort	Unknown words	Correctness
386.	<i>be recorded</i>	Passive voice misuse	Clarity
387.	, depending	Punctuation in compound/complex sentences	Correctness
388.	<i>The effective signal to noise ratio provided by machine learned models surpasses that of the raw measurements via learned feature extraction.</i>	Ungrammatical sentence	Correctness
389.	<i>The effective signal to noise ratio provided by machine learned models surpasses that of the raw measurements via learned feature extraction.</i>	Paragraph can be improved	Clarity
390.	an expected	Determiner use (a/an/the/this, etc.)	Correctness
391.	<del>assesses</del> → evaluates	Word choice	Engagement

392.	<i>For instance, our analysis techniques assess both expected SNR and an "algorithmic SNR," which assesses to what extent the model can increase the significance of the signal via learned functions.</i>	Paragraph can be improved	Clarity
393.	<del>side-channel</del> → side-channel	Misspelled words	Correctness
394.	<i>are uniquely tailored</i>	Passive voice misuse	Clarity
395.	<i>Training procedures and loss functions are vital for the success of neural network-based side channel attacks as they are uniquely tailored to the purpose of key recovery.</i>	Paragraph can be improved	Clarity
396.	<i>This</i>	Intricate text	Clarity
397.	<i>is prioritized</i>	Passive voice misuse	Clarity
398.	<i>This is particularly beneficial for scenarios where relative key ranking is prioritized over global probability calibration; it decreases guessing entropy by 20-30% relative to cross-entropy training.</i>	Paragraph can be improved	Clarity
399.	<i>Focal loss ratio results in 10-15% greater success rates for hard targets such as masked implementations.</i>	Paragraph can be improved	Clarity
400.	<del>channeling</del> → Channeling	Confused words	Correctness
401.	<del>;</del> → ;	Misuse of semicolons, quotation marks, etc.	Correctness
402.	<i>Multi-task models have comparable key recovery performance with 15-25% less trained traces, basically indicating better sample efficiency.</i>	Paragraph can be improved	Clarity
403.	<i>are trained</i>	Passive voice misuse	Clarity
404.	<i>new techniques must be applied</i>	Passive voice misuse	Clarity

405.	<i>As machine learning (ML) advances at a rapid pace and previously known side channel attacks become compounded, new techniques must be applied to counter the new enhanced predictability learned from trained neural networks.</i>	Paragraph can be improved	Clarity
406.	<del>Higher-Order</del> → Higher-Order	Misspelled words	Correctness
407.	<i>are split</i>	Passive voice misuse	Clarity
408.	<i>first-order masking can be undone</i>	Passive voice misuse	Clarity
409.	<i>For instance, first-order masking can be undone with as little as 1,000-5,000 traces, second-order masking needs greater than 10,000-50,000 traces, and third-order masking can exceed 100,000-500,000 traces to recover the key.</i>	Paragraph can be improved	Clarity
410.	<i>The exponential increase exists because the deeper the masking, the more advanced recombination functions the neural network must learn—and how the information overlaps across timestamps/mask shares.</i>	Paragraph can be improved	Clarity
411.	<i>In addition, the preprocessing needs become more advanced as well, often requiring centered product combining or greater statistical moments to appear as usable features.</i>	Paragraph can be improved	Clarity
412.	<i>Therefore, while it may be exploitable in theory, the practical requirements for data render such attacks unlikely to occur on systems that either have transient lifespans or are otherwise inaccessible by malicious actors.</i>	Paragraph can be improved	Clarity
413.	noise,	Punctuation in compound/complex sentences	Correctness

414.	<i>For example, random delay insertion increases temporal noise, yet falls short against alignment-invariant architectures.</i>	Paragraph can be improved	Clarity
415.	<i>randint</i>	Unknown words	Correctness
416.	<i>are positioned</i>	Passive voice misuse	Clarity
417.	<i>be shuffled</i>	Passive voice misuse	Clarity
418.	<i>are met</i>	Passive voice misuse	Clarity
419.	<i>This</i>	Intricate text	Clarity
420.	<i>be implemented</i>	Passive voice misuse	Clarity
421.	<i>circuit-level power differentials cannot be avoided</i>	Passive voice misuse	Clarity
422.	<i>the comparison</i>	Determiner use (a/an/the/this, etc.)	Correctness
423.	<i>be hijacked</i>	Passive voice misuse	Clarity
424.	<i>Our asserting tools allow for comparison of timing differentials based on various inputs, and we discover sub-microsecond differentials; however, power leakage can always be hijacked.</i>	Paragraph can be improved	Clarity
425.	<i>randint</i>	Unknown words	Correctness
426.	<i>This</i>	Intricate text	Clarity
427.	<del>by</del> → <i>to</i>	Wrong or missing prepositions	Correctness
428.	<del>ML-Based</del> → <i>ML-Based</i>	Misspelled words	Correctness
429.	<del>real-time</del> → <i>real-time</i>	Misspelled words	Correctness



430.	<del>time</del> ,	Punctuation in compound/complex sentences	Correctness
431.	<del>class</del> → Class	Improper formatting	Correctness
432.	<del>own</del>	Wordy sentences	Clarity
433.	<i>These latency and accuracy figures come from our own prototype detector, implemented in Python + PyTorch and benchmarked on an Apple M1 MacBook Pro.</i>	Paragraph can be improved	Clarity
434.	to invoke harsher mitigation strategies in response to attack detection dynamically	Inappropriate colloquialisms	Delivery
435.	<i>The detector assesses the statistical characteristics of power traces and detects anomalies that suggest an organized measurement attempt.</i>	Paragraph can be improved	Clarity
436.	<i>This feature makes life more difficult for the attacker, as he/she/they must go above and beyond to bypass all independent countermeasures at the same time.</i>	Paragraph can be improved	Clarity
437.	<del>network</del> → networks	Incorrect noun number	Correctness
438.	<i>Our system features inclusive support for synthetic side channel trace generation with customizable leakage features and countermeasures.</i>	Paragraph can be improved	Clarity
439.	<i>This</i>	Intricate text	Clarity
440.	the real	Determiner use (a/an/the/this, etc.)	Correctness
441.	<i>However, synthetic traces lack some physical properties of real hardware—manufacturing differences across chips, temperature-dependent leakage variations, and coupling between nearby circuit elements.</i>	Paragraph can be improved	Clarity

442.	<i>The best results seem to come from training on synthetic data and then fine-tuning with real traces instead of relying exclusively on either approach for data requirements and attack performance.</i>	Paragraph can be improved	Clarity
443.	<i>The visualization tools permit deeper insight into attack processes, attentional heat maps of trained networks, and areas where leakage often occurs.</i>	Paragraph can be improved	Clarity
444.	<del>def</del> → Def	Improper formatting	Correctness
445.	ge'	Unknown words	Correctness
446.	␣ → ;	Misuse of semicolons, quotation marks, etc.	Correctness
447.	␣ → ;	Misuse of semicolons, quotation marks, etc.	Correctness
448.	the model, or a model	Determiner use (a/an/the/this, etc.)	Correctness
449.	<i>Stripped down to the core, these tools give stable, comparable assessments across different approaches and reveal what filtering, architecture, and training results in the most successful outcomes for championed attacks.</i>	Paragraph can be improved	Clarity
450.	<del>side-channel</del> → side-channel	Misspelled words	Correctness
451.	<i>This research has demonstrated that machine learning drastically alters side channel attacks—both how one might attempt them and how one would defend against power analysis attacks.</i>	Paragraph can be improved	Clarity
452.	the incorporation	Determiner use (a/an/the/this, etc.)	Correctness

453.	to achieve cryptographic key recovery successfully	Inappropriate colloquialisms	Delivery
454.	<i>The results of implementation and analysis of this research suggest that regardless of attacker expertise, implementation time, and financial investment in attack development, incorporation of neural networks decreases the necessity of all three to successfully achieve cryptographic key recovery.</i>	Paragraph can be improved	Clarity
455.	<del>are able to</del> → can	Wordy sentences	Clarity
456.	, while	Punctuation in compound/complex sentences	Correctness
457.	<i>For example, CNNs are able to recover keys for first-order masked AES implementations with only 1000-2000 traces while typical differential power analysis requires 5000-10,000 traces.</i>	Paragraph can be improved	Clarity
458.	field,	Punctuation in compound/complex sentences	Correctness
459.	<i>This lower success threshold renders such attacks easier to accomplish out in the field where traces may only be able to be taken under certain circumstances.</i>	Paragraph can be improved	Clarity
460.	Architecture-Specific	Misspelled words	Correctness
461.	<i>Benefits of Architecture Specific Attacks: Each trained neural network architecture offers benefits for attacking based on the scenario.</i>	Paragraph can be improved	Clarity
462.	<i>For example, CNNs learn features on their own from aligned traces and achieve success rates between 70-85% on masked implementations.</i>	Paragraph can be improved	Clarity
463.	<del>achieve</del> → reach	Word choice	Engagement

464.	<i>LSTMs perform better with desynchronized samples since they achieve 60-75% success rates even with 1000 sample desynchronizations.</i>	Paragraph can be improved	Clarity
465.	<i>Attacks Work on All Implementations: The success of our implementation can attack AES, RSA, and ECC implementations regardless of whether countermeasures are employed.</i>	Paragraph can be improved	Clarity
466.	<i>such as second-order</i>	Paragraph can be improved	Clarity
467.	<i>relying → to rely</i>	Incorrect verb forms	Correctness
468.	<i>Empowering practical attacks: Where one would expect relying upon statistical findings, practical attacks that work against the statistical findings are vulnerable to ML attacks.</i>	Paragraph can be improved	Clarity
469.	<i>harder → more brutal</i>	Word choice	Engagement
470.	<i>Attacks are democratized: Deep learning is automated, meaning an attacker does not necessarily need prior knowledge of cryptography or feature engineering by hand.</i>	Paragraph can be improved	Clarity
471.	<i>We give the tools of implementation, and those wanting to experiment and attack others' implementations do not need knowledge of side channeling, nor even need to be experts; everyone from academic researchers to security auditors is at risk per our results.</i>	Paragraph can be improved	Clarity
472.	<i>Security Assessment: Enterprises must reassess the security of their systems using contemporary cryptography features, particularly those systems that rely on features that previously leveraged only classical defenses.</i>	Paragraph can be improved	Clarity
473.	<i>be made</i>	Passive voice misuse	Clarity

474.	<i>Defenses to Anticipate: Defenses for the future should be made from an ML perspective that may include adversarial training and randomization that are classically anti-ML.</i>	Paragraph can be improved	Clarity
475.	<i>been addressed</i>	Passive voice misuse	Clarity
476.	<i>Certifications to Expect: Existing security certifications must utilize ML testing methods to ensure that any and all attack vectors learned and explored for vulnerabilities have been addressed.</i>	Paragraph can be improved	Clarity
477.	<i>Defenses We've Introduced: We've shown that our ability to detect in real-time via ML has proven that we can implement active defenses in the middle of the attack.</i>	Paragraph can be improved	Clarity
478.	<i>Hardware-Software Integration: Solutions that depend on unified protective strategies such that algorithmic countermeasures presume software design as attack-aware.</i>	Paragraph can be improved	Clarity
479.	<del>Real World</del> → Real-World	Misspelled words	Correctness
480.	<del>side channel</del> → side-channel	Misspelled words	Correctness
481.	<i>The side channel security landscape has been transformed by the advent of deep learning.</i>	Passive voice misuse	Clarity
482.	<i>On the one hand, attacks using neural networks are easy and efficient; on the other hand, they enable ML for detection and trained responses for defense.</i>	Paragraph can be improved	Clarity
483.	<del>to facilitate</del> → , facilitating	Paragraph can be improved	Clarity
484.	<i>be assessed</i>	Passive voice misuse	Clarity
485.	<del>side channel</del> → side-channel	Misspelled words	Correctness

486.	<i>As embedded applications, IoT applications, and even cloud applications continue to rely on such cryptographic implementations more and more, these implementations need to be assessed for vulnerabilities to side channel attacks.</i>	Paragraph can be improved	Clarity
487.	<del>which generates</del> → <del>that generates</del>	Pronoun use	Correctness
488.	<i>This project illustrates how we need to question our prior assumptions of security now that we're in a world dominated by ML, and we need to conduct research which generates new assumptions of security that hold up against what today's neural networks can quickly ascertain.</i>	Paragraph can be improved	Clarity
489.	<del>Side-channel</del> → <del>Side-channel</del>	Misspelled words	Correctness
490.	<del>Side-channel</del> → <del>Side-channel</del>	Misspelled words	Correctness
491.	<del>side-channel</del> → <del>side-channel</del>	Misspelled words	Correctness
492.	<i>I choose you: Automated hyperparameter tuning for deep learning-based side channel analysis.</i>	Paragraph can be improved	Clarity
493.	<del>Side-channel</del> → <del>Side-channel</del>	Misspelled words	Correctness
494.	<del>side-channel</del> → <del>side-channel</del>	Misspelled words	Correctness
495.	<i>TransNet: Shift Invariant Transformer Network for Side Channel Analysis.</i>	Paragraph can be improved	Clarity
496.	<del>Side-channel</del> → <del>Side-channel</del>	Misspelled words	Correctness
497.	<i>ElectroMagnetic Analysis (EMA): Measures and Counter-Measures for Smart Cards..</i>	Paragraph can be improved	Clarity
498.	<del>..</del> → <del>., ...</del>	Closing punctuation	Correctness
499.	<del>are</del> → <del>is</del>	Faulty subject-verb agreement	Correctness

500.	<i>ss the power trace in time-disjointed, yet aligned, sequences as well. This helps capture any interdependencies that may be lost during a simple forward pass of the time series data. For example, when leakage from an operation that occurs after the viewed operation relies on an earlier read, such a...</i>		Originality
501.	<i>where <math>n</math> is the length of the trace and <math>m</math> is the size of</i>	Complete Measurement of All-window Footprints	Originality
502.	<i>metric.py</i> <code>def ecdsa_lattice_attack(self, traces: np.ndarray, signatures: List[Tuple[int, int]], messages: List[bytes], curve_name: str = 'secp256k1') -&gt; Optional[int]: """Lattice attack on ECDSA using partial nonce leaka...</code>		Originality
503.	<i>g, and compensating factors that greatly decrease an attack's success. For example, ideal lab settings present SNR values greater than 20 dB, stable triggering without trigger jitter, and controlled temperature. Real-world applications must deal with electromagnetic noise from other dev</i>		Originality
504.	<i>significantly based on the specific characteristics of the</i>	Supplier Capacity for 3/8 Inch Eye Bolts and Related Fasteners Solutions <a href="https://www.fastenerrigging.com/news/supplier-capacity-for-3-8-inch-eye-bolts-and-related-fasteners-solutions.html">https://www.fastenerrigging.com/news/supplier-capacity-for-3-8-inch-eye-bolts-and-related-fasteners-solutions.html</a>	Originality
505.	<i>Guessing entropy represents the average number of guesses</i>	A Survey of the Security and Privacy Measures for Anonymous Biometric Authentication Systems	Originality
506.	<i>IACR Transactions on Cryptographic Hardware and Embedded Systems, 2024</i>	GCKSign: Simple and efficient signatures from generalized compact knapsack problems	Originality
507.	<i>Analysis. IACR Transactions on Cryptographic Hardware and Embedded Systems,</i>	Locality-based Electromagnetic Leakage Assessment Using CNN	Originality

508.	<i>I choose you: Automated hyperparameter tuning for deep learning-based</i>	Stjepan Picek - researchr alias <a href="https://researchr.org/alias/stjepan-picek">https://researchr.org/alias/stjepan-picek</a>	Originality
509.	<i>2017). Convolutional Neural Networks with Data Augmentation Against Jitter-Based Countermeasures.</i>	Optimisation Method for Training Deep Neural Networks in Classification of Non- functional Requirements	Originality
510.	<i>Zaid, G., Bossuet, L., Habrard, A., &amp; Venelli, A.</i>	Noise2Clean: Cross-Device Side-Channel Traces Denoising with Unsupervised Deep Learning	Originality
511.	<i>Methodology for Efficient CNN Architectures in Profiling Attacks. IACR Transactions on Cryptographic Hardware and Embedded Systems, 2020</i>	Deep learning-based improved side-channel attacks using data denoising and feature fusion	Originality
512.	<i>Applications of machine learning techniques in side channel</i>	Feed-Forward Back-Propagation Neural Networks in Side-Channel Information Characterization	Originality
513.	<i>Focus is Key to Success: A Focal Loss Function for Deep Learning-based</i>	[Resource Topic] 2021/1408: Focus is Key to Success: A Focal Loss Function for Deep Learning-based Side-channel Analysis - Implementation - Ask Cryptography <a href="https://askcryp.to/t/resource-topic-2021-1408-focus-is-key-to-success-a-focal-loss-function-for-deep-learning-based-side-channel-analysis/15775">https://askcryp.to/t/resource-topic-2021-1408-focus-is-key-to-success-a-focal-loss-function-for-deep-learning-based-side-channel-analysis/15775</a>	Originality
514.	<i>In: Wiener, M. (eds) Advances in Cryptology — CRYPTO' 99. CRYPTO 1999. Lecture Notes in Computer Science,</i>	Luận án Một số phương pháp tấn công phân tích điện năng tiêu thụ hiệu quả sử dụng kỹ thuật xử lý tín hiệu và học máy - Luận văn, đồ án, đề tài tốt nghiệp <a href="https://luanvan.co/luan-van/luan-an-mot-so-phuong-phap-tan-cong-phan-tich-dien-nang-tieu-thu-hieu-qua-su-dung-ky-thuat-xu-ly-tin-hieu-va-hoc-may-77635/">https://luanvan.co/luan-van/luan-an-mot-so-phuong-phap-tan-cong-phan-tich-dien-nang-tieu-thu-hieu-qua-su-dung-ky-thuat-xu-ly-tin-hieu-va-hoc-may-77635/</a>	Originality



515.	<i>Kocher, P.C. (1996). Timing Attacks on Implementations of Diffie-Hellman, RSA, DSS, and Other Systems. In:</i>	Secured Hardware Design - an Overview	Originality
516.	<i>C. E. Shannon, "Communication in the Presence of Noise,</i>	Modelling of Echo Amplitude Fidelity for Transducer Bandwidth and Tfm Pixel Resolution	Originality
517.	<i><a href="https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&amp;arnumber">https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&amp;arnumber</a></i>	A Novel Multi-Factor Authentication Algorithm Based on Image Recognition and User Established Relations	Originality
518.	<i>A Unified Framework for the Analysis of Side-Channel Key Recovery Attacks. In:</i>	A note on the use of margins to compare distinguishers	Originality
519.	<i>2001). ElectroMagnetic Analysis (EMA): Measures and Counter-Measures for Smart Cards.</i>	Circuit-Variant Moving Target Defense for Side-Channel Attacks	Originality
520.	<i>and C. Paar, Eds., Lecture Notes in Computer Science, vol. 2523.</i>	Secured Hardware Design - an Overview	Originality
521.	<i>S. Mangard, E. Oswald, and T. Popp, Power Analysis Attacks: Revealing the Secrets of Smart Cards, Springer, 2007.</i>	Diseño de circuitos integrados y seguridad de circuitos criptográficos frente a ataques	Originality
522.	<i>The complete implementation of the techniques described in this paper</i>	Timing-driven placement for hierarchical programmable logic devices	Originality