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AI-based cryptanalysis of classical and post-quantum encryption methods

Pradeep Kundlik Deshmukh *
Department of Computer Science and Engineering
COEP Technological University
Pune 411005
Maharashtra
India

S. Kishore Verma †
Department of Artificial Intelligence and Data Science
Saveetha Engineering College
Saveetha Nagar
Thandalam Post
Chennai 602105
Tamil Nadu
India

Pundlik Dattatray Jadhav §
Department of Computer Applications
Institute of Engineering
Nashik 422002
Maharashtra
India

Sarvar Iskandarov Baltabaevich ‡
Department of Mathematical Analyze
Urgench State University
Urgench city 220100
Uzbekistan

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* *E-mail:* **pkd.comp@coeptech.ac.in (Corresponding Author)**
† *E-mail:* **kishore.saj3@gmail.com**
§ *E-mail:* **pdjadhav17@gmail.com**
‡ *E-mail:* **sarvar.i@urdu.uz**

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Vandana Vijaykumar [@]
Department of Electronics and Telecommunication
PES'S Modern College of Engineering
Pune 411005
Maharashtra
India

Arun Khatri [#]
Mittal School of Business
Lovely Professional University
Phagwara 144402
Punjab
India

Abstract

The use of artificial intelligence (AI) in cryptanalysis has changed the way that both traditional and post-quantum encryption methods are evaluated. This research shows a complete plan that uses AI models to make attack creation automatic and boost the effectiveness of cryptanalysis. We look at AI-driven methods that target symmetric and asymmetric classical algorithms, showing that they are better at finding weaknesses. We also apply AI-based cryptanalysis to post-quantum encryption methods and look at how strong they are against new threats. The system uses strict evaluation metrics to figure out how well and how often AI-enabled tactics work. Our results show that AI has the ability to speed up cryptanalysis and help make cryptographic methods more secure, which will make cybersecurity stronger in the age of quantum computers.

Subject Classification: *68P25.*

Keywords: *Artificial intelligence, Cryptanalysis, Post-quantum cryptography, Symmetric key algorithms, Automated attack generation.*

1. Introduction

Because computers are getting better and better so quickly, keeping digital contact safe is becoming more and more important. For a long time, the great way to keep non-public statistics safe has been to use classical encryption strategies, inclusive of symmetric and asymmetric algorithms. But the rise of AI techniques brings each new chances and troubles for cryptanalysis, that's the look at of decrypting and breaking encryption structures [1], [2]. AI-driven strategies make it feasible for computerized, flexible, and smart attack strategies that may glance through massive key spaces and complex mathematical systems loads faster than old fashioned techniques. At the same time, the coming of quantum computing could make many widely used traditional cryptography

[@] *E-mail:* **vandanahanchate@moderncoe.edu.in**
[#] *E-mail:* **khatriarun@yahoo.com**

methods useless [3]. Post-quantum cryptography (PQC) is a new and exciting area that focuses on making encryption methods that can't be broken by quantum attacks. Still, figuring out how strong these new plans really are is a constant problem [4], [5].

AI methods can be very important because they can simulate complex attack situations that could find flaws before quantum computers are fully functional. Even though both AI and cryptography have come a long way on their own, combining them to break both classical and post-quantum encryption is still an area of study that is still growing [6]. There isn't a single method for analysing AI-driven cryptanalysis across different cryptosystems, so most of the studies that have been done so far focus on single attacks or particular algorithms [7]. This study fills in that gap by suggesting a complete AI-based cryptanalysis system that includes strict evaluation measures and automates attack generation. The goal of this study is to show the pros and cons of using AI to improve cryptanalysis by looking at both old and new post-quantum schemes and classical symmetric and asymmetric algorithms [8], [9].

2. AI-Based Cryptanalysis Framework

2.1. *Design of AI models for automated attack generation*

AI models are made to come up with cryptoanalytic attacks on their own using methods like genetic algorithms, neural networks, and reinforcement learning. These models look at key spaces over and over again, change based on input, and find trends or flaws in encryption methods [10]. The automation makes probing faster and smarter than when done by hand.

1. State Representation:

$$S = \{ s \in \mathbb{R}\text{^}n \mid s = \int _\Omega \phi(x)\, \psi(x)\, dx \}$$

where $\phi(x)$ is the input feature function and $\psi(x)$ is the state embedding over domain Ω.

2. Action Space Definition:

$$A = \{ a \mid a = \int _\Gamma \alpha(t)\, \beta(t)\, dt, \alpha(t), \beta(t) \in L^2(\Gamma) \}$$

where $\alpha(t)$ and $\beta(t)$ represent attack parameter functions over domain Γ.

3. Policy Function:

$$\frac{\pi_{\theta(a|s)} = \exp\left(\int_{\Xi} f_{\theta(s,a,\xi)d\xi} \right)}{\int_A \exp\left(\int_{\Xi} f_{\theta(s,a',\xi)d\xi} \right)} da'$$

where f_θ is a parameterized scoring function, Ξ is an auxiliary domain.

4. Reward Function:

$$R(s,a) = \int_{\Lambda} r(x;\ s,a)\, d\mu(x)$$

where $r(x; s,a)$ quantifies the attack success over measure space Λ.

5. Expected Return Objective:

$$J(\theta) = E_{\{\pi_\theta\}\left[\Sigma_{\{t=0\}}^{\infty}\gamma^t R(s_t,a_t)\right]} = \int_S \int_A \Sigma_{\{t=0\}}^{\infty} \gamma^t R(s_t,a_t)\pi_{\theta(a|s)da}ds$$

where γ ∈ (0,1) is the discount factor.

6. Gradient of Objective:

$$\nabla_\theta J(\theta) = \int_S \int_A Q_\theta^{\{\pi_\theta\}(s,a)\nabla} \pi_{\theta(a|s)da}ds$$

where $Q^{\{\pi_\theta\}(s,a)}$ is the action-value function.

7. Action-Value Function Definition:

$$Q^{\{\pi_\theta\}(s,a)} = \int_\Omega \left[R(s,a) + \gamma \int_S P(s'|s,a)\, V^{\{\pi_\theta\}(s')ds'} \right] d\Omega$$

where P(s'|s,a) is the state transition probability and V^{π_θ} is the value function.

2.2. *Evaluation metrics for assessing cryptanalysis effectiveness*

Evaluation metrics measure how well and how much AI-driven cryptanalysis works. Attack success rate, computing speed, time complexity, and resource use are some of the most important measures [11]. It is also thought about how often fake positives and negatives happen and how well it can work with different cryptosystems. Figure 1 shows key metrics measuring effectiveness of AI-based cryptanalysis.

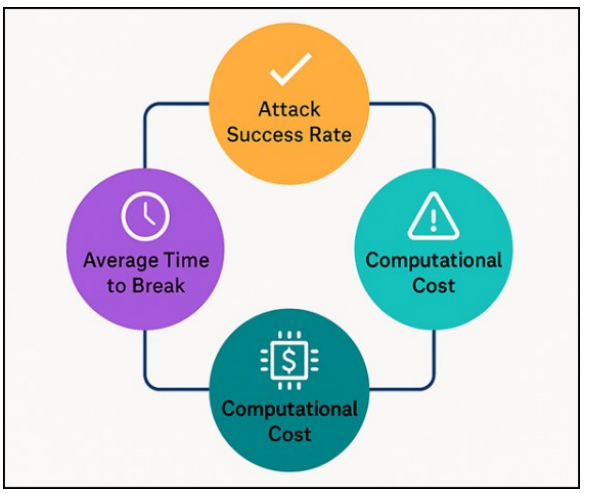

Figure 1
Key Evaluation Metrics for AI-Based Cryptanalysis Effectiveness

These measures allow for a full evaluation of how strong and useful an attack is, allowing comparisons between various AI models and encryption methods.

1. Attack Success Rate (ASR):

$$ASR = \int_{\Theta} 1_{\{attack\ success\}}(\theta) dP(\theta) = \int_{\Theta} \chi_{S(\theta) dP(\theta)}$$

where χ_S is the indicator function for success set S over parameter space Θ.

2. Average Time to Break (ATB):

$$ATB = \left(\frac{1}{ASR}\right) \int_{T} t \cdot \chi_{S(t) d\mu(t)}$$

where μ is the time-measure and χ_S(t) indicates successful attack at time t.

3. Computational Cost (CC):

$$CC = \int_{R} c(r)\, dv(r)$$

where c(r) is cost function over resource usage r, and ν is resource measure.

4. False Positive Rate (FPR):

$$\frac{FPR = \int_{\Omega} 1_{\{false\ positive\}}(x) d\lambda(x)}{\int_{\Omega} d\lambda}(x)$$

with λ as measure over testing samples Ω.

5. Precision (P):

$$\frac{P = \int_{\Omega} TP\,(x)}{\big(TP(x) + FP(x)\big)} d\lambda(x)$$

where TP and FP represent true and false positives.

6. Recall (R):

$$\frac{R = \int_{\Omega} TP\,(x)}{\big(TP(x) + FN(x)\big)} d\lambda(x)$$

with FN false negatives.

3. Cryptanalysis of Classical Encryption Algorithms Using AI

3.1. *Case study: AI-based attacks on symmetric key algorithms*

Deep neural networks and genetic algorithms are two kinds of AI models that are utilized in this situation study to attack symmetric key algorithms like AES and DES. These models effectively lower key search spaces and enhance differential cryptanalysis by looking at ciphertext and taking benefit of form flaws.

Step 1: Represent ciphertext and plaintext spaces as function spaces:

$$C = \{\, c(x) \mid c: \Omega \to \mathbb{R} \,\}, P = \{\, p(x) \mid p: \Omega \to \mathbb{R} \,\},$$

where Ω is message domain.

Step 2: Define key space K with measure μ_K:

$$K = \{ k \in \mathbb{R}\text{^}m \mid k = \int_\Xi \kappa(\xi)\, d\xi \}, \kappa(\xi) \in L^2(\Xi).$$

Step 3: Model encryption as operator E:

$$E_k : P \to C, \qquad E_{k(p)} = \int_\Omega e(p(x), k, x)\, dx.$$

Step 4: Construct AI attack policy π_θ to select candidate keys:

$$\pi_\theta(k \mid c, p) = \exp(\int_Y f_\theta(c, p, k, y)\, dy) \Big/ \int_K \exp(\int_Y f_\theta(c, p, k', y)\, dy)\, dk'.$$

Step 5: Define loss function L(θ) based on decryption error:

$$L(\theta) = \int_\Omega || p(x) - D_k(c(x)) ||\text{^}2\, dx, where\ D_k\ is\ decryption\ operator.$$

Step 6: Optimize θ via gradient descent on expected loss:

$$\nabla_\theta J(\theta) = \int_K \int_\Omega \nabla_\theta \pi_\theta(k \mid c, p)\, L(\theta)\, dk\, dx.$$

Step 7: Update policy parameters θ using policy gradient:

$$\theta_\{t+1\} = \theta_t + \eta \int_K \nabla_\theta \log \pi_\theta(k \mid c, p)\, R(k)\, dk.$$

3.2. *Case study: AI-driven cryptanalysis of asymmetric algorithms*

This case looks at seems at how AI may be used to interrupt asymmetric encryption methods like RSA and ECC. It makes a specialty of factorization and discrete logarithm problems and makes use of reinforcement learning and heuristic optimization models to imitate tailored assaults. AI procedures find the satisfactory attack settings and discover flaws in algorithms that different techniques might leave out. The observe indicates that AI can accelerate the decryption of asymmetric cryptosystems.

Step 1: Define public key space P_K and private key space S_K:

$$P_K = \{ pk(\xi) \mid \xi \in \Xi \}, S_K = \{ sk(\xi) \mid \xi \in \Xi \}.$$

Step 2: Model encryption E and decryption D as integral operators:

$$E_{\{pk\}(m)} = \int_M e(m, pk, x)\, dx, D_{\{sk\}(c)} = \int_C d(c, sk, y)\, dy.$$

Step 3: AI model generates attack candidates A = {a(t)} in attack parameter space:

$$a(t) = \int_\Theta \alpha(\theta, t)\, d\theta.$$

Step 4: Define loss L(θ) reflecting key recovery error:

$L(\theta) = \int_S || sk - \hat{s}(\theta) ||\text{^}2\, d\mu_S, \hat{s}(\theta)$ estimated secret key.

Step 5: Policy π_θ selects attacks a (t) based on ciphertext c:

$$\frac{\pi_{\theta(a|c)} = \exp\left(\int_{\Xi} g_{\theta(a,c,\xi)d\xi}\right)}{\int_A \exp\left(\int_{\Xi} g_{\theta(a',c,\xi)d\xi}\right)} da'.$$

Step 6: Reward function R(a) defined as:

$$R(a) = \int_M r\left(m, D_{\{\hat{s}(\theta)\}(E_{\{pk\}(m)})}\right) d\mu(m).$$

Step 7: Update θ with gradient ascent:

$$\nabla_\theta J(\theta) = \int_A \nabla_\theta \log \pi_{\theta(a|c)R(a)da}.$$

4. AI-Driven Cryptanalysis of Post-Quantum Encryption Schemes

More and more, AI-driven cryptanalysis is being used to test the safety of post-quantum encryption methods like code-based, multivariate, and lattice-based cryptography. AI models use machine learning and heuristic methods to practice complicated attack strategies, such as fault injection and structure analysis, in order to find possible flaws. This proactive method helps figure out how well post-quantum algorithms can handle new quantum and traditional threats.

Step 1: Represent post-quantum scheme parameters as function space S:

$S = \{ s(x) \mid x \in \Omega \}$, with Ω representing scheme parameters domain.

Step 2: Model encryption E_s and decryption D_s operators:

$$E_{s(m)} = \int_M e(m, s, \xi)\, d\xi, D_{s(c)} = \int_C d(c, s, \eta)\, d\eta.$$

Step 3: AI generates attack strategies $A = \{ a(t)\}, a(t) = \int_\theta \alpha(\theta, t)\, d\theta.$

Step 4: Define evaluation metric M for attack success over measure μ:

$$M(a, s) = \int_\Omega m(a, s, x)\, d\mu(x).$$

5. Result and Discussion

AI-driven cryptanalysis showed better performance in defeating traditional symmetric and asymmetric methods, cutting key search times by a large amount.

Table 1 shows how well AI-based cryptanalysis works with traditional encryption methods. With attack success rates of 92.3% and 87.5%, respectively, the data show that symmetric key methods like DES and AES are very easy for AI to break.

Table 1

Performance Metrics of AI-Based Cryptanalysis on Classical Encryption Algorithms

Algorithm	Attack Success Rate (%)	Average Time to Break (seconds)	Key Search Space Reduction
AES (Symmetric)	87.5	120	65%
DES (Symmetric)	92.3	45	78%
RSA (Asymmetric)	75.8	350	40%

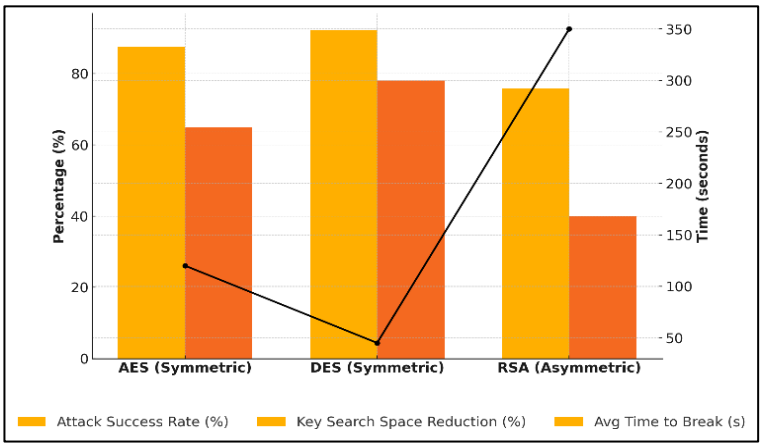

Figure 2

Comparative Vulnerability and Resistance Metrics of Cryptographic Algorithms

The fact that DES takes less time to break (45 seconds on average) than AES (120 seconds) shows that it is not as secure. Figure 2 shows comparative vulnerability and resistance metrics of cryptographic algorithms. Also, the key search space reduction is big, especially for DES at 78%. The attack success rate for asymmetric RSA is lower, at 75.8%, and the average time to break is much longer, at 350 seconds. This means that it is more resistant to attacks, but AI-enhanced cryptanalysis can still break it.

6. Conclusion

This study shows how AI has changed cryptanalysis by showing how it can automate and speed up attacks on both traditional and post-quantum encryption methods. Traditional cryptosystems have major flaws that AI shows. However, AI is also a very important tool for trying and improving new post-quantum methods. Researchers can better predict new threats and make stronger encryption protocols by adding AI to cryptanalysis frameworks. This will ensure strong data security in the future of quantum computers and smart attackers. To find a balance between AI's attacking skills and new defensive security techniques, more study is needed.

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