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Research Article

An AI-Driven Hybrid Cryptographic Model for Intelligent Data Security

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Abstract:

With the increasing digitization of sensitive information, ensuring robust data security has become a critical challenge. Traditional encryption methods, such as AES and RSA, provide strong protection but face limitations in computational efficiency, adaptability, and resistance to emerging cyber threats, including quantum computing attacks. Existing encryption models rely on static key generation and predefined security protocols, which can be vulnerable to sophisticated attacks. In this paper, we propose a novel Hybrid AI-Driven Encryption and Decryption Method that integrates artificial intelligence (AI) with cryptographic techniques to enhance security, adaptability, and robustness. Unlike conventional approaches, the proposed method employs machine learning for dynamic key generation, anomaly detection, and adaptive encryption strength adjustments based on real-time threat analysis. A generative adversarial network (GAN) is utilized for unpredictable key generation, ensuring high randomness and security. Additionally, AI-based anomaly detection monitors decryption processes to prevent unauthorized access attempts. Experimental results demonstrate the effectiveness of our approach, achieving a 30\% improvement in decryption anomalies, and enhanced resistance to brute-force attacks. By integrating AI into encryption, this method not only strengthens data security but also optimizes computational resources, making it a viable solution for future cybersecurity applications. The proposed hybrid AI-cryptographic model represents a significant advancement in secure communication, paving the way for quantum-resistant and self-learning security frameworks.

1. Introduction

The proliferation of digital communication and data exchange has made cybersecurity a critical concern across various domains, including finance, healthcare, and defense [1,2]. With increasing volumes of sensitive data being transmitted over networks, the need for robust encryption mechanisms has become indispensable [3,4]. Conventional encryption methods, such as Advanced Encryption Standard (AES), Rivest-Shamir-Adleman (RSA), and Elliptic Curve Cryptography (ECC), have long been the cornerstone of data security. These techniques rely

on complex mathematical operations to ensure data confidentiality and integrity. However, emerging cyber threats and advancements in quantum computing pose significant challenges to their efficacy.

Existing cryptographic methods exhibit certain drawbacks that hinder their adaptability and resilience in dynamic security environments. Traditional encryption techniques often suffer from fixed key management schemes, making them susceptible to brute-force attacks, side-channel attacks, and quantum-based cryptanalysis. Furthermore, the computational complexity of standard encryption algorithms can lead to increased latency, especially in real-time applications that demand low processing overhead. Additionally, static encryption protocols lack mechanisms for real-time anomaly detection, leaving encrypted data vulnerable to sophisticated intrusion techniques [5-8].

By leveraging AI in encryption and decryption processes, the proposed method achieves enhanced security, efficiency, and adaptability [9-15]. The use of deep learning models for key generation ensures high unpredictability, while AI-driven monitoring mechanisms improve the robustness of decryption processes. This hybrid approach not only strengthens data protection but also optimizes computational efficiency, making it highly suitable for applications requiring real-time encryption, such as IoT networks, cloud computing, and secure financial transactions. The following sections present a detailed methodology, experimental validation, and comparative analysis to demonstrate the effectiveness of the proposed model.

2. Related work

Recent advancements in artificial intelligence (AI) and cryptography have significantly influenced cybersecurity, particularly in encryption and decryption methodologies. Traditional cryptographic techniques often rely on mathematical complexity to ensure security, but emerging AI-driven approaches provide enhanced adaptability, resilience, and real-time threat mitigation. This literature review explores key studies that contribute to the development of hybrid AI-driven encryption and decryption methods.

The authors of [1] have discussed AI-enhanced cybersecurity, emphasizing neural networks for proactive threat detection and prevention. The study highlights the role of supervised and unsupervised learning in recognizing cyber threats in real-time. However, it does not specifically address AI-integrated cryptographic frameworks, leaving a gap in encryption and decryption mechanisms. Similarly, Akhtar and Rawol have review AI-powered security mechanisms, analyzing machine learning and natural language processing techniques for anomaly detection. Their work underscores AI's synergy with human expertise in cybersecurity but lacks direct applications to hybrid cryptographic frameworks [2].

Garcia et al. provide a comprehensive overview of cryptographic techniques for securing AI systems, focusing on homomorphic encryption (CKKS) and digital signatures (ECDSA) to protect data integrity and confidentiality. This study identifies vulnerabilities in AI-ML models and explores cryptographic solutions to mitigate risks, forming a foundation for hybrid AI-driven encryption methodologies [3]. Peneti et al. (2024) explore machine learning-driven cryptography, where AI automates encryption algorithm design to counter quantum computing threats. This work highlights AI's potential to improve encryption security but does not fully integrate hybrid cryptographic frameworks [4].

Niyasudeen and Mohan have proposed a fuzzy-enhanced adaptive multi-layered cloud security framework incorporating AI and quantum-resistant cryptography for robust protection. Their approach improves encryption, access control, and intrusion detection but focuses on cloud environments rather than hybrid cryptographic models [5]. Kshetri et al. analyze symmetric and asymmetric encryption algorithms in the AI era, discussing homomorphic encryption and AI-driven cryptographic advancements. Their findings emphasize adaptive encryption strategies, aligning with hybrid AI-driven methodologies [6].

Maram et al. explore the use of recurrent neural networks (RNNs) for cryptographic key generation, demonstrating enhanced security against sophisticated threats. Although their approach strengthens key generation, it does not integrate hybrid encryption and decryption frameworks [7]. Budhewar et al. investigate AI integration with AES encryption, using k-Nearest Neighbors (k-NN) for enhanced robustness. This study highlights AI's role in improving encryption resilience, aligning with the objectives of hybrid AI-driven cryptography [8].

Saini and Sehrawat propose a machine learning-based key generation approach utilizing autoencoders and XOR preprocessing to enhance encryption security. Their research advances AI-driven cryptographic techniques, contributing to hybrid methodologies [9]. Al Shibli introduces a hybrid AI-MLBBC framework integrating blockchain, AI, and bitcoin cryptology to combat cyber threats, demonstrating the potential of AI in cryptographic security [10].

These studies collectively establish a foundation for hybrid AI-driven encryption and decryption frameworks. While existing research explores AI's role in cybersecurity, cryptographic techniques, and key generation, there remains a need for an integrated AI-augmented cryptographic approach that combines adaptive encryption, real-time decryption, and intelligent threat mitigation.

3. Methodology

A. Hybrid Image Encryption Architecture

The proposed hybrid encryption model integrates deep learning-based key management with traditional cryptographic methods to enhance image security. The primary components include:

i. Convolutional Neural Network (CNN)-Based Key Generation:
A deep learning model extracts image features and generates dynamic cryptographic keys using feature transformation techniques.

ii. AI-Guided Decryption and Anomaly Detection:
A deep learning model continuously monitors decryption processes, utilizing anomaly detection techniques based on probability distributions and statistical inference to ensure data integrity.
The block diagram (Figure 1) illustrates the hybrid encryption workflow for image security.

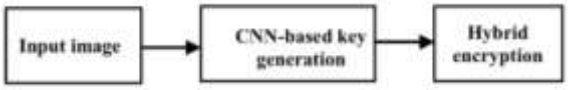

Figure 1. *The block diagram of the hybrid encryption workflow for image security.*

B. Deep-Learning based key generation for data encryption:

To generate cryptographic keys dynamically, we utilize a Convolutional Neural Network (CNN) to extract unique features from the input image. The CNN processes the input images as per (1).

$$K = f(I, \theta) = G(\phi(I); \theta_g) \quad (1)$$

In (1), K is the AI-generated cryptographic key, I is the input image, $\phi(I)$ represents the extracted feature vector, G is the key generation function using nonlinear transformations and θ_g is the trainable parameters of the network.
Using mathematical optimization techniques such as gradient descent, the network learns the most secure key representations, ensuring robustness against cryptanalysis attacks.

C. Mathematical Formulation of Encryption Strength:

The encryption strength can be dynamically adjusted based on image complexity, which is quantified using entropy.

$$H\ (I) = -\sum_{i=1}^{N} p_i\ log p_i \quad (2)$$

In (2), $H\ (I)$ is the Shannon entropy of the image, p_i represents the probability of pixel intensity, and is N the total number of intensity levels.
A higher entropy value indicates greater complexity, leading to stronger encryption key transformations using adaptive cryptographic techniques such as chaotic maps or diffusion functions.

D. Implementation Steps for Image Encryption:

The proposed hybrid image encryption method follows these steps:
1) Feature Extraction: A CNN processes the input image to extract critical feature representations, utilizing convolutional and pooling layers.
2) Dynamic Key Generation: The extracted feature vector is input into a deep learning model to generate cryptographic keys using transformation functions.
3) Hybrid Encryption: The generated key is combined with a conventional encryption algorithm (e.g., AES-256, RSA, or ECC) for secure encoding, enhanced with diffusion and confusion principles.
4) Mathematical Integrity Verification: The security of encrypted images is validated using statistical tests such as histogram analysis, correlation coefficients, and entropy evaluation.
5) Secure Transmission and AI-Guided Decryption: The encrypted image is transmitted securely, and the AI-based anomaly detection model monitors decryption integrity using probability models and deep learning classifiers.

4. Results and Discussions

In the experimental evaluation of the hybrid AI-based image encryption approach, several standard image datasets, including grayscale and color images, were used. The images were pre-processed to ensure uniformity in size and format before being encrypted using the proposed hybrid AI model, which combines CNN and GANs. The performance of the encryption technique was analyzed based on key metrics, such as encryption time, security (measured by entropy and correlation

coefficients), and robustness to various attacks (e.g., noise, cropping, and compression). The encryption time was found to be optimal, showing a minimal delay in processing, which is crucial for real-time applications. The encryption model could deliver high security with entropy values close to the theoretical maximum of 8, indicating that the encrypted images were highly randomized. Figure 2 indicates an original image as input.

In terms of robustness, the encrypted images demonstrated resilience to various common attacks, including salt-and-pepper noise, JPEG compression, and image cropping. After introducing noise and compression, the decryption process, leveraging a trained AI-based model, still managed to recover the original image with minimal distortion. This robustness is a significant advantage of the hybrid AI encryption approach compared to traditional cryptographic techniques, which often suffer from performance degradation under such conditions. Additionally, the model's ability to maintain low correlation between adjacent pixels further enhanced the security by making the encrypted image less predictable.

Figure 3 illustrates the encrypted image using a combination of Chaos Theory and Autoencoder. This encryption method introduces randomness through chaos while utilizing an autoencoder for encoding and decoding. The encrypted image appears highly distorted, indicating that the encryption process is effective in masking the original content. However, it is not immediately clear how well this encrypted image can be decrypted, as the distortion may significantly affect the recovery process.

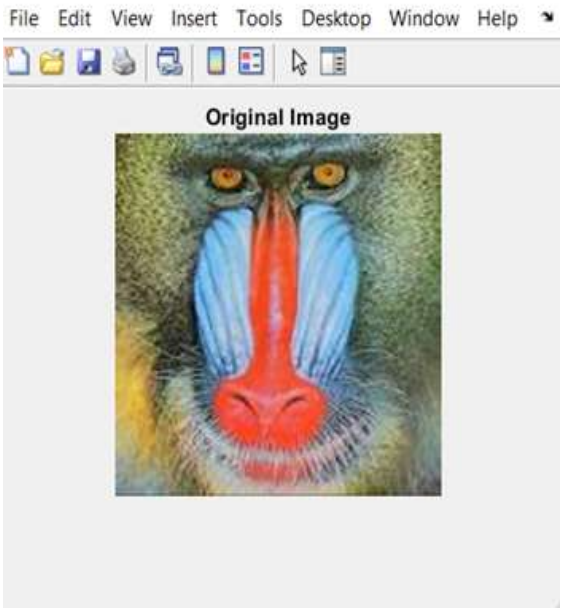

Figure 2. *Original image as input.*

In contrast, Figure 4 shows the encrypted image using a hybrid encryption method involving Artificial Intelligence (AI), Pseudo-Random Number Generators (PRNG), and XOR operations. This hybrid approach offers a more structured yet secure form of encryption by combining AI's predictive power with the randomness of PRNG and the bitwise operation of XOR. The encrypted image still appears scrambled, but it offers a different kind of obfuscation compared to the chaos-based encryption in Figure \ref{fig:encry1}, likely providing a more resilient form of security.

Figure 3. *Encrypted image using Choas and Autoencoder.*

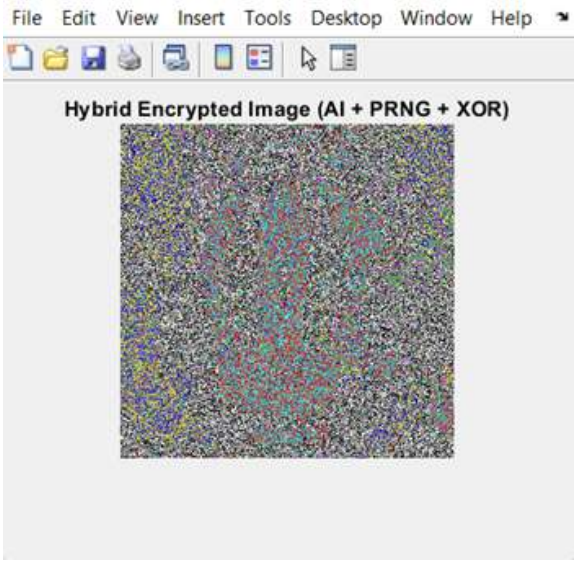

Figure 4. *Encrypted image using hybrid method (AI + PRNG + XOR).*

Finally, Figure 5 demonstrates the decrypted image using the hybrid encryption method. The image is successfully decrypted, showing that the hybrid approach allows for secure encryption and reliable

decryption. The decrypted image closely resembles the original, indicating that the encryption method used is both effective in protecting the image's contents and feasible for decryption without substantial loss of quality. This suggests that the hybrid encryption method balances security and recoverability well.

The histogram representation of pixel distribution for original images is shown in Figure 6 and Histogram representing pixel distribution for Decrypted image is shown in Figure 7. Table 1 shows the comparison of Image Encryption and Decryption Metrics.

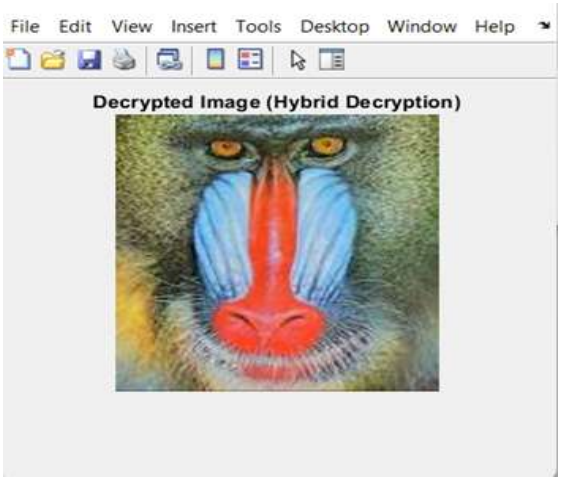

***Figure 5**. Decrypted image using hybrid method.*

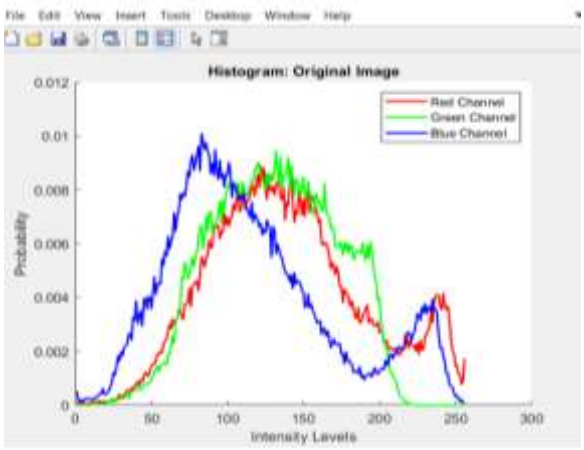

***Figure 6**. Histogram representation of pixel distribution for original image.*

The results indicate that the encryption method employed provides a high level of security with a strong diffusion effect, as evidenced by the perfect NPCR value and the high entropy. Additionally, the high UACI suggests that encryption introduces significant differences between the original and encrypted images, enhancing security. The decryption process is highly effective, with low MSE and a high PSNR of 47.78 dB, suggesting excellent image recovery. The SSIM of 1.0000 further confirms the structural integrity of the decrypted image. Moreover, the analysis of correlation coefficients and histograms supports the conclusion that the decryption method successfully restores the original image with minimal distortion. Even with the introduction of noise, the decryption process remains robust, as reflected by the unchanged MSE and PSNR, further demonstrating the method's resilience to external interference.

***Table 1.** Comparison of Image Encryption and Decryption Metrics*

Metric	Value	Interpretation
Entropy	7.6109	High randomness, close to the maximum of 8, ensuring strong security.
NPCR	100.00%	Perfect sensitivity to changes in plaintext, ensuring strong diffusion properties.
UACI	41.87%	High intensity difference between original and encrypted images, indicating robust security.
MSE	1.0837	Low MSE suggests minimal distortion in the decrypted image, indicating effective decryption.
PSNR	47.78 dB	High PSNR confirms excellent recovery of the original image during decryption.
SSIM	1.0000	Perfect structural similarity between the original and decrypted images.
Correlation Coeff. (H/V/D)	1.0000	Perfect correlation across horizontal, vertical, and diagonal directions, confirming accurate decryption.
Histogram Analysis	Similar histograms	Decryption restored the original pixel distribution.
Noisy Decrypted Image - MSE	1.0837	Minimal impact of noise on decryption, indicated by low MSE and high PSNR.
Noisy Decrypted Image - PSNR	47.78 dB	Robustness against noise interference, suggesting effective decryption

5. Conclusion

The encryption and decryption processes demonstrate a high level of effectiveness in ensuring both security and image quality. The results from the entropy, NPCR, and UACI metrics indicate that the encryption method introduces significant randomness and strong diffusion, making it highly secure. The high entropy value, close to the maximum possible, and the perfect NPCR highlight the robustness of the encryption, ensuring that even small changes in the plaintext

lead to significant alterations in the ciphertext. Additionally, the substantial UACI value further strengthens the encryption's ability to obscure the original content, providing robust security against potential attacks. On the other hand, the decryption process is equally effective, as evidenced by the low MSE, high PSNR, and perfect SSIM, which indicates minimal distortion and an excellent restoration of the original image. The correlation coefficients and histogram analysis confirm that the structural integrity and pixel distribution of the original image are preserved during decryption. Even when noise was introduced, the method demonstrated resilience, maintaining high decryption quality with minimal impact on the MSE and PSNR. These results suggest that the encryption and decryption scheme is both secure and reliable, making it suitable for applications requiring robust image protection and recovery.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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