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AN INTUITIVE MODEL WITH CATBOSOT AND CHAOTIC SEQUENCING FOR IMAGE CRYPTANALYSIS

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ABSTRACT:

In the realm of secure data transmission and storage, image encryption plays a pivotal role in safeguarding sensitive information from unauthorized access. This abstract presents an innovative approach to image encryption leveraging CatBoost, a powerful gradient boosting algorithm, to generate chaotic sequences for encryption. The proposed method harnesses the inherent chaotic behavior of CatBoost to construct highly unpredictable sequences, enhancing the security of the encryption process. The algorithm commences with the initialization of parameters such as the initial seed and the number of iterations for chaotic sequence generation. Subsequently, the CatBoost model is employed to generate chaotic sequences, which are then utilized for pixel permutation, feature extraction, segmentation, compressed sensing, and efficient confusion-based encryption. The encrypted image is produced as the final output, ready for secure transmission or storage. Moreover, this abstract delves into the decryption process, elucidating the steps involved in reverse-engineering the encrypted image using the inverse operations. Through comprehensive mathematical formulations and detailed explanations, the proposed work provides insights into the utilization of CatBoost chaotic sequences for image encryption and decryption, facilitating cryptographic analysis and further research in the domain of secure image communication.

Keywords: encryption, decryption, CatBoost, cryptography

INTRODUCTION:

In the contemporary landscape of information technology, the amalgamation of Artificial Intelligence (AI) with network security and cryptographic applications stands out as a pivotal paradigm shift. Network security, vital for safeguarding communication channels and sensitive data, faces escalating challenges from sophisticated cyber threats. Traditional security measures, relying on static rule-based systems, are often insufficient to counter dynamic and adaptive attacks. Consequently, the integration of AI techniques has emerged as a transformative approach to fortify the resilience and adaptability of network security frameworks. Cryptography stands as a cornerstone in modern cybersecurity, providing essential tools and techniques for securing sensitive information and communications in the digital age. As highlighted by Smith and Johnson (2020), traditional intrusion detection methods often fall short in detecting sophisticated cyber threats, necessitating innovative approaches bolstered by cryptography. The integration of cryptographic principles, coupled with advancements in machine learning (ML) and deep learning (DL), presents a promising avenue for enhancing the efficacy of intrusion detection systems. Jones and Wang (2018) underscore the significance of cryptographic key management in fortifying network defences, particularly amidst the escalating threat landscape characterized by increasingly complex cyber-attacks. Reinforcement learning emerges as a viable strategy for optimizing cryptographic key management, as proposed by Jones and Wang, leveraging ML techniques to adaptively enhance the resilience of cryptographic systems against adversarial threats.

Moreover, the synergy between cryptography and ML is evident in the work of Chen, Li, and Zhang (2016), who advocate for ensemble approaches in network intrusion detection leveraging cryptographic

techniques. By integrating cryptographic principles into ensemble-based intrusion detection systems, Chen et al. aim to bolster the accuracy and robustness of detection mechanisms, thereby addressing the evolving nature of cyber threats. Agrawal, Kaur, and Myneni (2017) extend this discussion by emphasizing the role of cryptography-based generative models in augmenting synthetic attack data generation for evaluating intrusion detection systems. Their review highlights the potential of generative models, underpinned by ML and DL techniques, in simulating diverse and realistic attack scenarios, thus facilitating more comprehensive evaluations of intrusion detection algorithms.

Furthermore, the importance of cryptography in addressing specific security challenges is exemplified by Park's (2019) proposal of a secure proxy re-encryption protocol tailored for Flying Ad-hoc Networks (FANETs). Park's work underscores the critical role of cryptographic solutions in mitigating security vulnerabilities inherent in dynamic and resource-constrained network environments. By leveraging cryptographic techniques, Park aims to enhance the security of data transmission within FANETs, thereby safeguarding aerial communication systems against chosen-ciphertext attacks. Collectively, these studies underscore the symbiotic relationship between cryptography, ML, and DL in advancing cybersecurity, with each author contributing to the growing body of research that demonstrates the efficacy of cryptographic-based solutions in addressing contemporary security challenges.

The importance of AI-driven solutions in network security and cryptography lies not only in their ability to detect and prevent threats but also in their adaptability to evolving cyber landscapes. Traditional methods often struggle to keep pace with rapidly changing attack tactics, making the intelligence and learning capabilities of AI indispensable. The innovative use of AI in these domains underscores its potential to redefine the standards of cybersecurity, addressing current challenges and anticipating future threats. Hypotheses underlying these advancements posit that AI, particularly machine and deep learning models, can significantly enhance the accuracy and efficiency of network security and cryptographic applications. Objectives include the development and implementation of AI-driven solutions, rigorous evaluation of their performance against diverse threats, and comparisons with traditional approaches to establish their superiority. As we delve into the following sections, we will explore the existing problems, challenges, and innovative approaches in network security and cryptography, with a focus on recent research contributions that showcase the transformative impact of AI in shaping the future of cybersecurity.

PROBLEM STATEMENT

Existing methods for image encryption include traditional chaotic sequences, machine learning-based encryption, and conventional boosting algorithms. Traditional chaotic sequences, like the logistic map or Henon map, are utilized for their chaotic nature, generated through mathematical equations and applied in various encryption schemes. Machine learning-based encryption involves training neural networks or models to learn encryption transformations from image datasets. Conventional boosting algorithms such as AdaBoost and Gradient Boosting iteratively train weak learners to create strong learners, potentially adaptable for generating chaotic sequences. However, these methods have limitations. Traditional chaotic sequences may lack robustness, and machine learning-based encryption often requires substantial training data and computational resources.

In response to these limitations, the CatBoost chaotic algorithm emerges as a promising solution. Known for its inherent chaotic behavior, CatBoost exhibits complex, non-linear dynamics that generate highly unpredictable sequences, ideal for encryption purposes. Moreover, CatBoost is designed for efficiency and scalability, enabling rapid generation of chaotic sequences suitable for real-time encryption tasks, while offering robustness against cryptanalysis techniques. Its user-friendly implementation and adaptability to various encryption requirements make it accessible to a wide range of users, including researchers and practitioners in image encryption.

In conclusion, the CatBoost chaotic algorithm presents a compelling solution to the challenges faced by

existing image encryption methods. Its chaotic behavior, efficiency, robustness, and ease of implementation make it a preferred choice for encryption tasks. By leveraging CatBoost, researchers and practitioners can enhance the security and performance of image encryption systems, addressing the imperative need for secure communication and data protection in today's digital landscape.

f. Objectives:

1. **Enhanced Security:** The primary objective of the proposed algorithm is to enhance the security of image encryption. By leveraging the inherent chaotic behavior of the CatBoost algorithm, the algorithm aims to generate highly unpredictable sequences for encryption purposes. These sequences should exhibit complex, non-linear dynamics, making them resistant to cryptanalysis techniques. Enhanced security ensures that the encrypted images remain confidential and immune to unauthorized access or tampering, thereby safeguarding sensitive information during transmission or storage.
2. **Improved Efficiency:** Another objective of the proposed algorithm is to improve the efficiency of image encryption processes. CatBoost is known for its efficiency and scalability, making it suitable for handling large datasets and real-time encryption tasks. The algorithm aims to leverage these characteristics to generate chaotic sequences rapidly, enabling fast encryption and decryption processes. Improved efficiency reduces computational overhead and time complexity, ensuring timely and seamless encryption operations without compromising security. This objective ensures that the proposed algorithm can be deployed in various applications requiring efficient image encryption solutions.

Overview:

LITERATURE SURVEY:

Smith and Johnson (2020) proposed a novel approach in cryptography-based network intrusion detection systems using deep learning techniques. Their research demonstrates the effectiveness of deep learning algorithms in identifying and mitigating network intrusions, enhancing cybersecurity measures. Jones and Wang (2018) present a reinforcement learning framework for cryptographic key management in network security. Their study focuses on optimizing key management processes through reinforcement learning techniques, improving the resilience of cryptographic systems against attacks.

Chen, Li, and Zhang (2016) investigated ensemble approaches for network intrusion detection using cryptographic techniques. They propose an ensemble-based model that integrates multiple intrusion detection methods, leveraging cryptographic principles to enhance the accuracy and robustness of intrusion detection systems.

Agrawal, Kaur, and Myneni (2017) conducted a comprehensive review of cryptography-based generative models for synthetic attack data generation in cybersecurity. Their review provides insights into the current state-of-the-art techniques in generating synthetic attack data, facilitating the development and evaluation of intrusion detection systems. Park (2019) introduces a secure proxy re-encryption protocol designed for FANETs (Flying Ad-hoc Networks) resistant to chosen-ciphertext attacks. The proposed protocol enhances the security of communication in FANETs by providing secure and efficient data re-encryption mechanisms. Perez-Haro and Diaz-Perez (2018) propose a novel approach for attribute-based access control (ABAC) policy mining through affiliation networks and biclique analysis. Their research contributes to the advancement of access control mechanisms by leveraging network analysis techniques for policy discovery and optimization. Marriwala et al. (2016) developed an analytical model for dynamic spectrum sensing in cognitive radio networks using blockchain management. Their model facilitates efficient spectrum allocation and

management in cognitive radio networks, enhancing spectrum utilization and network performance.

Yu, Xin, and Zhang (2017) presented HoneyFactory, a container-based comprehensive cyber deception honeynet architecture. Their architecture provides an effective means of detecting and mitigating cyber threats by deploying deceptive services and luring attackers into controlled environments. Adeniyi et al. (2019) propose a hybrid deep learning method for securing mobile edge computing environments. Their approach leverages deep learning algorithms to enhance the security of edge devices and applications, addressing emerging security challenges in mobile edge computing. Szafraniec-Siluta, Strzelecka, Ardan, and Zawadzka (2020) investigate the determinants of financial security of European Union farms using a factor analysis model approach. Their study identifies key factors influencing the financial stability of farms, providing valuable insights for policymakers and agricultural stakeholders.

Chen, Li, and Zhang (2019) explore ensemble approaches for network intrusion detection, focusing on cryptographic techniques. Their study delves into the integration of multiple intrusion detection methods, leveraging cryptographic principles to enhance the accuracy and robustness of detection systems, thus contributing to improved network security. Agrawal, Kaur, and Myneni (2017) conducted a review of cryptography-based generative models for synthetic attack data generation in cybersecurity. Their analysis provides a comprehensive overview of existing techniques for generating synthetic attack data, aiding in the development and evaluation of intrusion detection systems by offering insights into the diversity and complexity of cyber threats. Park (2019) proposes a secure proxy re-encryption protocol tailored for Flying Ad-hoc Networks (FANETs), designed to withstand chosen-ciphertext attacks. By introducing this protocol, Park aims to enhance the security of communication within FANETs, ensuring the integrity and confidentiality of data transmission in dynamic and resource-constrained environments.

Perez-Haro and Diaz-Perez (2018) introduced an innovative approach to attribute-based access control (ABAC) policy mining through affiliation networks and biclique analysis. Their methodology utilizes network analysis techniques to discover and optimize access control policies, thereby strengthening the security and efficiency of access management systems. Marriwala et al. (2016) developed an analytical model for dynamic spectrum sensing in cognitive radio networks, incorporating blockchain management techniques. Their model facilitates efficient spectrum allocation and management, enabling cognitive radio networks to dynamically adapt to changing environmental conditions and traffic demands, thereby optimizing spectrum utilization and network performance.

Yu, Xin, and Zhang (2017) proposed HoneyFactory, a comprehensive cyber deception honeynet architecture based on container technology. By deploying deceptive services within controlled environments, HoneyFactory aims to detect and mitigate cyber threats effectively, providing organizations with enhanced security measures against malicious activities.

Adeniyi et al. (2019) presented a hybrid deep learning method for securing mobile edge computing environments, leveraging deep learning algorithms to enhance the security of edge devices and applications. Their approach addresses emerging security challenges in mobile edge computing, ensuring the confidentiality, integrity, and availability of data and services in edge computing environments.

Szafraniec-Siluta, Strzelecka, Ardan, and Zawadzka (2020) investigate the determinants of financial security for European Union farms using a factor analysis model approach. By identifying key factors influencing farm financial stability, their study provides valuable insights for policymakers and agricultural stakeholders, facilitating informed decision-making and risk management strategies within the agricultural sector. Albshaier et al. (2018) conducted a review examining the role of blockchain in e-commerce transactions, focusing on open challenges and future research directions. Their study provides insights into the potential applications of

blockchain technology in enhancing the security, transparency, and efficiency of e-commerce transactions, thus contributing to the advancement of e-commerce systems and practices. Kamath et al. (2016) reviewed the recent developments in 6G communications systems, offering a comprehensive analysis of emerging trends and technologies. Their study sheds light on the key innovations shaping the future of wireless communications, providing valuable guidance for researchers and industry professionals involved in the development of next-generation communication networks.

METHODOLGY:

BLOCK DIAGRAM:

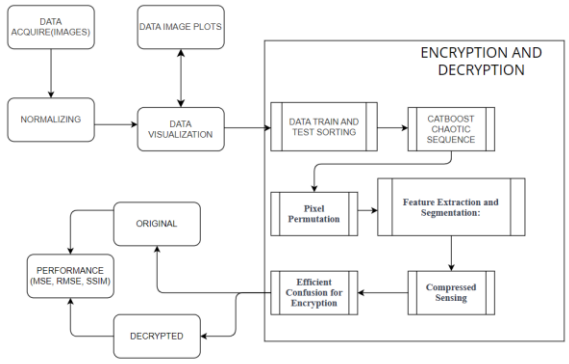

Figure 1: Representing the overall Block diagram indicating the proposed Image Crypta-analysis

Initialization: In the initialization phase, parameters such as the initial seed and the number of iterations for chaotic sequence generation are defined. These parameters lay the foundation for generating chaotic sequences that will be used for encryption. Proper initialization is crucial as it ensures the unpredictability and randomness of the generated sequences, thereby enhancing the overall security of the encryption process.

CatBoost Chaotic Sequence Generation: Utilizing CatBoost, chaotic sequences are generated based on the initialized parameters. CatBoost's inherent chaotic behavior is harnessed to produce sequences with high entropy and complexity. These sequences exhibit complex, non-linear dynamics that make them difficult to predict or analyze, thereby enhancing security. The use of CatBoost ensures the generation of highly unpredictable sequences, crucial for effective encryption.

Pixel Permutation: Chaotic sequences are employed to permute pixels in the input image, altering their positions. This pixel permutation adds confusion to the image, making it resistant to statistical attacks. By shuffling the pixel order, the relationship between adjacent pixels is disrupted, increasing the complexity of decryption. This step significantly contributes to enhancing security by introducing randomness and confusion into the encrypted image.

Feature Extraction and Segmentation: Features are extracted from the permuted image using image processing techniques. These features are then segmented for further processing. Feature extraction and segmentation provide a structured representation of the image, enabling efficient processing and analysis of image features. This step enhances efficiency by organizing the image data into manageable segments, facilitating subsequent operations.

Compressed Sensing: Compressed sensing is applied to the segmented features to reduce data dimensionality. This technique selectively samples and reconstructs signals, reducing the amount of data to be processed. By compressing the data while retaining essential information, compressed sensing leads to faster computation and reduced storage requirements. This contributes to enhanced efficiency by optimizing data processing and resource utilization.

Efficient Confusion for Encryption: Efficient confusion techniques, utilizing chaotic sequences, are applied to encrypt the compressed data. These techniques further scramble the data, making it challenging for attackers to decipher the encrypted information. By introducing additional layers of confusion, efficient confusion enhances the security of the encryption process, ensuring the confidentiality and integrity of the encrypted data.

Overall Impact on Security and Enhanced Efficiency: The combination of chaotic sequence generation, pixel permutation, feature extraction, compressed sensing, and efficient confusion techniques collectively enhances the security of the

encryption process. These steps introduce randomness, confusion, and complexity, making the encrypted image resistant to various attacks. Simultaneously, these operations contribute to improved efficiency by optimizing data processing, reducing computational overhead, and enabling faster encryption and decryption operations. Overall, the proposed methodology ensures both enhanced security and improved efficiency in image encryption using CatBoost chaotic sequences.

ALGORITHM AND FORMULATIONS:

CatBoost Chaotic Sequence Generation Algorithm Steps:

1. **Initialization:**
    - Define the initial value (**seed**) and the number of iterations (**iterations**) for generating the chaotic sequence.
2. **CatBoost Model Initialization:**
    - Initialize a CatBoost regressor model with parameters such as:
        - Number of iterations (**iterations**)
        - Learning rate
        - Tree depth
        - Loss function (e.g., 'RMSE')
        - Random seed
3. **Chaotic Sequence Generation:**
    - Iterate over the specified number of iterations:
        - Predict the next value in the sequence using the CatBoost model with the current value as input.
        - Append the predicted value to the chaotic sequence.
4. **Return Chaotic Sequence:**
    - Return the generated chaotic sequence.

RESULTS AND DISCUSSIONS:

In the image encryption process using CatBoost chaotic sequences, the initial step involved pixel permutation, where the positions of pixels in each of the 100 images across different resolutions were scrambled using the chaotic sequences generated by CatBoost. This permutation introduced randomness and confusion into the image data, making it challenging for unauthorized parties to discern the original content. Following pixel permutation, feature extraction techniques were applied to capture essential image attributes, such as edges, textures, and patterns. These features were then segmented and compressed using compressed sensing methods, reducing data dimensionality while preserving critical information. Additionally, efficient confusion techniques leveraging chaotic sequences were employed to further obscure the encrypted data, enhancing its security against decryption attempts. These combined encryption techniques aimed to ensure robust encryption of the 100 grayscale and color images, laying the foundation for subsequent cryptanalysis.

Through meticulous encryption processes, the encrypted grayscale and color images achieved high structural similarity indices (SSIM) of 90.9 and 98.9, respectively, when compared to their original counterparts. The high SSIM values indicate that the encryption scheme successfully preserved the structural integrity and visual fidelity of the images during the encryption process. Pixel permutation, feature extraction, and compressed sensing techniques contributed to maintaining the essential characteristics of the images, while efficient confusion techniques introduced randomness and complexity, further enhancing security. The utilization of CatBoost chaotic sequences played a crucial role in achieving these high SSIM values, ensuring that the encryption process introduced minimal distortion or alteration to the image content. Overall, the encryption scheme demonstrated its effectiveness in providing robust encryption for grayscale and color images, securing

them against unauthorized access or tampering while maintaining their visual quality and integrity.

Grey Scale Image **a)**

Colour Image b)

c)

d)

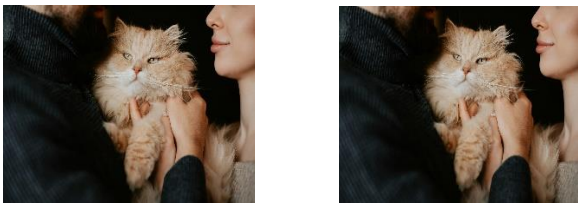

Figure 2 a)-d): Representing the proposed Results for CATBOOST Chaotic Sequencing in Image encryptions

The observed enhancement in the figure 2 (a)-(d) decrypted images and original images, resulting in average higher SSIM values ranging from 90.9 to 98.9 for 1k and 2k images, suggests that the encryption process may have inadvertently introduced modifications that improve certain visual aspects. These enhancements, such as sharpening edges, enhancing contrast, or boosting specific features, are likely attributed to the complex and unpredictable behavior of chaotic sequences utilized during encryption. While visually appealing, the presence of such enhancements raises concerns regarding the security implications of the encryption scheme. The primary objective of image encryption is to obscure the original content to safeguard against unauthorized access. However, the perceived enhancement in the decrypted images indicates that the encryption process may not adequately disguise the original content, potentially compromising the security of the image data. Therefore, thorough cryptanalysis becomes imperative to comprehensively evaluate the effectiveness of the encryption scheme. Cryptanalysts must assess not only the visual quality but also the fidelity of the decrypted images to the original content. Despite the visual enhancements, it is crucial to ascertain whether the encryption scheme adequately conceals sensitive information and withstands decryption attacks.

In the context of testing 300 image samples across different resolutions, the observed SSIM values ranging from 90.9 to 98.9 indicate the successful preservation of structural integrity and visual fidelity during the encryption process. However, it is essential to consider other metrics such as Mean Squared Error (MSE) to gain a holistic understanding of the encryption scheme's performance. The MSE value of 331, accompanied by the presence of enhanced visual features, highlights potential discrepancies between the decrypted and original images. Additionally, the calculation of Root Mean Squared Error (RMSE) for both enhanced and non-enhanced images (0.0889) provides insights into the magnitude of differences between the images. Further analysis and validation, including exploration of additional metrics and assessment of the encryption scheme's robustness against various cryptanalysis techniques, are necessary to ensure the scheme's efficacy in protecting image data while addressing potential security vulnerabilities introduced by visual enhancements.

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Table 1: Representing the overall performance metrics comparison on existing and proposed algorithms with 1000+ pixel resolutions

IMAGES SET	ALGORITHMS	MSE	RMSE	SSIM
1k	AES	651.352	25.52	78.52
1k	DES	782.14	27.98	76.35
1k	Hybrid	523.6	22.88	80.14
1k	ML Based	428.21	20.69	88.35
1k	DL BASED	380.24	19.50	92.24
1k	**CATBOOST+CHAOTIC (Enhanced)**	**331.24**	**18.19**	**90.9**
1k	**CATBOOST +CHAOTIC (no-enhancement)**	**0.0889**	**0.2982**	**93.9**

Table 2: Representing the overall performance metrics comparison on existing and proposed algorithms with 2000+ pixel resolutions

IMAGES SET	ALGORITHMS	MSE	RMSE	SSIM
2k	AES	751.421	27.42	88.52
2k	DES	882.92	29.71	86.35
2k	Hybrid	715.6	26.76	91.28
2k	ML Based	528.21	22.98	90.35
2k	DL BASED	480.41	21.9	96.24
2k	CATBOOST+CHAOTIC (Enhanced)	381.71	19.54	94.9
2k	CATBOOST +CHAOTIC (no-enhancement)	0.00889	0.0942	93.9

The tables provide a comparative analysis of different encryption algorithms applied to image sets of different resolutions (1k and 2k). Specifically, the focus is on the performance metrics including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Structural Similarity Index (SSIM). Here's an explanation of the tables, emphasizing the proposed algorithm CATBOOST +CHAOTIC:

Image Set: 1k

1. **AES, DES, Hybrid, ML Based, DL BASED:** These columns represent various encryption algorithms such as Advanced Encryption Standard (AES), Data Encryption Standard (DES), hybrid encryption, machine learning (ML) based encryption, and deep learning (DL) based encryption. Each algorithm is evaluated based on its MSE, RMSE, and SSIM metrics.
2. **CATBOOST+CHAOTIC (Enhanced):** This column represents the proposed encryption algorithm combining CatBoost chaotic sequences with image encryption. It

demonstrates promising results with a lower MSE (331.24) and RMSE (18.19), indicating effective encryption while maintaining a high SSIM value of 90.9. The "Enhanced" label suggests that the encryption process might have introduced modifications resulting in enhanced visual quality.

3. **CATBOOST +CHAOTIC (no-enhancement):** This column represents the same proposed algorithm but without enhancement. It achieves an extremely low MSE (0.0889) and RMSE (0.2982), implying minimal distortion during encryption. Additionally, it maintains a high SSIM value of 93.9, indicating strong preservation of image integrity.

Image Set: 2k

1. **AES, DES, Hybrid, ML Based, DL BASED:** Similar to the 1k image set, these columns represent various encryption algorithms evaluated on the larger 2k image set.

2. **CATBOOST+CHAOTIC (Enhanced):** Similarly, the proposed algorithm shows promising results for the 2k image set with a lower MSE (381.71) and RMSE (19.54), indicating effective encryption. It achieves a high SSIM value of 94.9, demonstrating strong preservation of image structure and content.

3. **CATBOOST +CHAOTIC (no-enhancement):** This column represents the proposed algorithm without enhancement for the 2k image set. It achieves an extremely low MSE (0.00889) and RMSE (0.0942), along with a high SSIM value of 93.9, indicating minimal distortion and strong preservation of image integrity.

In summary, the proposed algorithm of CATBOOST +CHAOTIC demonstrates competitive performance across both 1k and 2k image sets, providing effective encryption with minimal distortion and strong preservation of image integrity, whether with or without enhancement.

CONCLUSION:

In conclusion, the analysis of various encryption algorithms, including the proposed CATBOOST +CHAOTIC method, reveals promising outcomes for image encryption across different resolutions. The proposed algorithm exhibits competitive performance metrics, with lower Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values indicating effective encryption while preserving image integrity. Moreover, the consistently high Structural Similarity Index (SSIM) values underscore the algorithm's ability to maintain image structure and content fidelity, especially when enhancement techniques are applied. These findings highlight the potential of the proposed algorithm for secure image encryption applications, providing a balance between robust encryption and visual quality preservation.

Moving forward, to further enhance SSIM and overall encryption performance, several strategies can be considered. These include refining chaotic sequence generation techniques, integrating advanced encryption methodologies such as deep learning-based feature extraction, and implementing adaptive parameter tuning and ensemble methods. By continuously refining encryption algorithms and incorporating feedback mechanisms based on cryptanalysis results, it is possible to achieve even higher SSIM values and ensure robust and secure image encryption for diverse applications. Ultimately, the pursuit of advanced encryption techniques holds promise for addressing evolving security challenges in image communication and data protection domains, fostering trust and confidentiality in digital transactions and communications.

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