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AN QUASI INTERPOLATIVE APPORACH OF MLP CLASSIFIER FOR IMAGE RECONSTRUCTION WITH CRYPTANALYSIS

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Abstract:

In the realm of image reconstruction and cryptanalysis, the development of accurate and efficient classifiers plays a pivotal role in deciphering encrypted images and restoring them to their original form. In this study, we propose an innovative interpolative approach of a multilayer perceptron (MLP) classifier tailored specifically for image reconstruction tasks involving cryptanalysis. Our method aims to achieve superior performance in both decrypting encrypted images and accurately reconstructing them, leveraging the flexibility and adaptability of MLPs in learning complex patterns and relationships within the data.

The proposed interpolative MLP classifier is designed to operate in two distinct modes: one for processing real (unencrypted) images and another for decrypting encrypted images. In the real image mode, the classifier learns to recognize and classify various features and patterns present in unencrypted images, achieving a training accuracy of 99% through rigorous training on a diverse dataset. This high level of accuracy ensures the reliable reconstruction of real images, enabling the classifier to faithfully restore images even in the presence of noise or distortion.

In the cryptanalysis mode, the interpolative MLP classifier is tasked with decrypting encrypted images by discerning hidden patterns and structures obscured by encryption algorithms. Through an innovative interpolation technique, the classifier adapts its learned representations from real images to decrypt encrypted counterparts, effectively bridging the gap between the two domains. By exploiting the inherent similarities between real and encrypted images, the classifier achieves remarkable performance in image reconstruction, with decryption accuracy matching or exceeding that of conventional cryptanalysis methods.

Key to the success of our approach is the custom design of the MLP architecture, tailored to accommodate the unique characteristics of image data and encryption schemes. The network architecture is optimized to handle high-dimensional image data while incorporating advanced activation functions and regularization techniques to prevent overfitting and enhance generalization. Additionally, the training process is augmented with specialized loss functions and optimization strategies tailored specifically for image reconstruction and cryptanalysis tasks, ensuring robust convergence and optimal performance.

Through extensive experimentation and evaluation on benchmark datasets, our interpolative MLP classifier demonstrates superior performance compared to existing approaches in both image reconstruction and cryptanalysis. With a training accuracy of 99% in both real and decrypted cases, our method establishes a new benchmark for accuracy and efficiency in image reconstruction tasks involving cryptanalysis, offering promising implications for various applications in security, forensics, and image processing.

Keywords: Cryptanalysis, Deciphering, Multilayer Perceptron (MLP), Encryption.

INTRODUCTION:

Image encryption plays a crucial role in safeguarding sensitive visual information from unauthorized access during transmission and storage. With the proliferation of digital imagery across various domains, ensuring the confidentiality and integrity of image data has

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become paramount. Encryption algorithms employ sophisticated techniques to scramble image pixels or transform image representations in such a way that the original content remains unintelligible without the decryption key. However, the security of image encryption schemes is constantly challenged by advancements in cryptanalysis techniques, necessitating the development of robust encryption methods that can withstand potential attacks.

Numerous image encryption algorithms have been proposed in the literature, leveraging chaos-based systems, cryptographic primitives, and mathematical transformations to obscure image content effectively. However, the effectiveness of these encryption schemes is contingent upon their resilience to cryptanalysis attacks. Recent studies have highlighted vulnerabilities in various image encryption algorithms, exposing weaknesses that could compromise the security of encrypted images. For instance, algorithms based on chaotic maps, permutation-diffusion techniques, and combined cryptographic primitives have been subjected to cryptanalysis, revealing susceptibilities to differential attacks, brute-force methods, and statistical analysis.

The need for enhanced image encryption methods that can withstand sophisticated cryptanalysis techniques is evident. While existing encryption algorithms provide a level of security, there remains a research gap in developing encryption schemes capable of resisting various cryptanalysis attacks while maintaining high computational efficiency. Addressing this gap requires innovative approaches that leverage advanced cryptographic techniques and machine learning methodologies to design encryption algorithms with superior security and performance metrics.

In this context, the proposed work aims to bridge this research gap by introducing a novel interpolative approach of a multilayer perceptron (MLP) classifier for image reconstruction with cryptanalysis. The utilization of MLP classifiers offers several advantages, including their ability to learn complex patterns and relationships within image data, adaptability to different encryption schemes, and flexibility in handling high-dimensional input data. By integrating MLP classifiers into the image reconstruction process, the proposed approach seeks to enhance the accuracy and efficiency of decrypting encrypted images while mitigating vulnerabilities to cryptanalysis attacks.

The contributions of this work include the development of a custom-designed MLP classifier tailored specifically for image reconstruction tasks involving cryptanalysis. The interpolative approach enables the classifier to adapt its learned representations from real images to decrypt encrypted counterparts, effectively bridging the gap between the two domains. Additionally, the proposed work introduces new performance metrics for evaluating the effectiveness of image encryption algorithms, including structural similarity index (SSIM), peak signal-to-noise ratio (PSNR), mean squared error (MSE), and root mean squared error (RMSE). These metrics provide comprehensive insights into the quality and fidelity of reconstructed images, facilitating a more nuanced assessment of encryption algorithm performance.

Through extensive experimentation and evaluation on benchmark datasets, the proposed approach aims to demonstrate superior performance compared to existing image encryption methods. By enhancing the security and resilience of encrypted images against cryptanalysis attacks while maintaining computational efficiency, the proposed work offers promising implications for applications in secure image transmission, storage, and communication.

LIERATURE SURVEY:

Ahmad et al. proposed an image encryption algorithm based on combined chaos for a Body Area Network (BAN) system, highlighting the importance of secure image transmission in healthcare applications. Their work underscores the need for robust encryption schemes to protect sensitive medical data, especially in wireless communication environments where data privacy is critical [1]. Zhu et al. conducted cryptanalysis on an image encryption algorithm utilizing a novel chaos-based S-box. By identifying vulnerabilities in the encryption scheme, their study emphasizes the importance of rigorous security analysis to assess the resilience of encryption algorithms against various cryptanalysis techniques [2]. Another work by Zhu et al. focused on improving the security of an image encryption scheme by enhancing cryptanalysis techniques using combined 1D chaotic maps. This study highlights the iterative nature of encryption algorithm development, where continuous enhancements are necessary to address emerging security threats and vulnerabilities [3]. Li et al. analyzed a permutation-diffusion-based lightweight chaotic image encryption scheme using the Differential Cryptanalysis (CPA) method. Their research underscores the significance of lightweight encryption algorithms in resource-constrained environments, such as embedded systems and Internet of Things (IoT) devices [4]. Wen et al. investigated the security of an image encryption algorithm based on DNA encoding and spatiotemporal chaos. By breaking the encryption scheme, their study emphasizes the need for encryption algorithms resilient to cryptanalysis attacks leveraging advanced computational techniques [5].

Zhang and Yu conducted a security analysis of a Latin-Bit Cube-based image chaotic encryption algorithm, shedding light on the vulnerabilities inherent in certain encryption schemes. Their findings contribute to the understanding of encryption algorithm weaknesses and the importance of developing robust cryptographic solutions [6]. Dou and Li performed cryptanalysis on a new color image encryption scheme using a combination of 1D chaotic maps, revealing vulnerabilities that could compromise image security. Their study underscores the dynamic nature of cryptographic research, where cryptanalysis plays a crucial role in enhancing algorithm security [7]. Lin and Wu conducted cryptanalysis and proposed improvements for a chaotic map-based image encryption system using plaintext-related permutation and diffusion techniques. This work highlights the iterative process of encryption scheme development, where cryptanalysis findings drive enhancements to algorithm security [8]. Jin et al. proposed a novel hybrid secure image encryption scheme based on the shuffle algorithm and the hidden attractor chaos system. Their research demonstrates the exploration of innovative encryption techniques to address security challenges and improve algorithm robustness against cryptanalysis attacks [9]. Huang et al. conducted a cryptanalysis of a Latin Cubes-based image cryptosystem, uncovering vulnerabilities that could compromise image security. This study emphasizes the importance of continual evaluation and improvement of encryption algorithms to mitigate emerging security threats [10].

Hernández-Díaz et al. proposed a JPEG images encryption scheme using elliptic curves and a new S-box generated by chaos. Their work focuses on enhancing the security of image encryption techniques by leveraging mathematical concepts such as elliptic curves and chaos theory to strengthen cryptographic primitives [11]. Wen et al. conducted a security analysis of a color image encryption algorithm using fractional-order chaos, providing insights into the robustness of encryption schemes against cryptanalysis attacks based on chaotic dynamics. Their research contributes to the exploration of advanced encryption techniques to enhance algorithm security in image communication systems [12]. Wen et al. introduced a security-enhanced image communication scheme using a cellular neural network, emphasizing the integration of neural network-based approaches with cryptographic techniques to enhance image security. This study underscores the interdisciplinary nature of image encryption research, where insights from diverse fields drive innovation in cryptographic solutions [13]. Fan et al. conducted cryptanalysis of a new chaotic image encryption technique based on multiple discrete dynamical maps, highlighting vulnerabilities that could compromise image security. Their findings underscore the importance of rigorous security analysis to identify and address potential weaknesses in encryption algorithms [14]. Rahman et al. proposed a high-security image encryption algorithm based on a novel simple fractional-order memristive chaotic system, aiming to enhance the resilience of encryption schemes against cryptanalysis attacks. Their research contributes to the exploration of novel chaotic systems for developing robust encryption solutions in image security [15].

Feng et al. introduced an image encryption algorithm based on plane-level image filtering and discrete logarithmic transform, exploring innovative approaches to enhance image security. Their work underscores the importance of integrating diverse cryptographic techniques to improve algorithm robustness against cryptanalysis attacks [16]. Lawnik et al. investigated chaos-based cryptography for text encryption using image algorithms, exploring the integration of image processing techniques with cryptographic primitives for secure communication.

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This study highlights the potential of cross-disciplinary research in advancing encryption solutions for diverse applications [17]. Algazy et al. conducted a differential analysis of a cryptographic hashing algorithm, emphasizing the importance of evaluating cryptographic primitives' security properties against differential cryptanalysis attacks. Their work contributes to the understanding of cryptographic hash function security and resilience against cryptanalysis techniques [18]. Lone et al. conducted cryptanalysis and proposed an improved image encryption scheme using elliptic curve and affine Hill cipher, demonstrating the effectiveness of combining multiple cryptographic techniques to enhance image security. Their research highlights the iterative nature of encryption algorithm development, where continual improvements are essential to address emerging security challenges [19]. Zhang et al. performed cryptanalysis of an image encryption algorithm based on a 2D hyperchaotic map, identifying vulnerabilities that could compromise image security. Their findings underscore the importance of rigorous security analysis to ensure the resilience of encryption algorithms against cryptanalysis attacks leveraging chaotic dynamics [20].

METHODOLOGY:

Our research aims to develop an integrated image security model leveraging techniques such as (k, n)-threshold visual secret sharing, flip extended visual cryptography, and quantum-inspired methods. The objective is to enhance image security, protecting against unauthorized access and tampering, thus ensuring the confidentiality and integrity of visual data in real-time applications like secure communication channels and image storage systems.

Additionally, we seek to improve the efficiency and robustness of the encryption process by incorporating advancements in quantum-inspired techniques demonstrated by El-Latif et al. (2021). These methods will enhance the resilience of image encryption against sophisticated attacks while minimizing computational overhead.

Moreover, we aim to enhance the capability to detect and localize image forgery through improved watermarking techniques inspired by the work of Salim et al. (2022). This holistic approach strengthens the security posture of image-based systems, ensuring integrity, authenticity, and confidentiality across various applications.

Integration with CatBoost Algorithm:

1. **Block Diagram:**
   - Encryption: The CatBoost algorithm is integrated into the encryption process to improve classification accuracy and enhance security. After partitioning the processed image into 64x64 pixel blocks, CatBoost is utilized to classify each block, determining its content or features. This classification information can be used to adjust encryption parameters or to selectively apply encryption techniques based on block content, enhancing overall security.
   - Decryption: Similarly, CatBoost classification can aid in the decryption process by assisting in the identification and classification of decrypted blocks. This classification information can guide the post-decryption adjustment process, helping to accurately reconstruct the original image by efficiently handling the rearrangement of blocks and removal of data processing effects.
2. **Algorithm concept:**
   - Encryption: In addition to the existing encryption process, CatBoost classification is integrated to classify image blocks before encryption. This involves training the CatBoost classifier on labeled image data to recognize patterns or features indicative of specific content types or characteristics.
   - Decryption: During decryption, CatBoost classification assists in identifying and categorizing decrypted blocks, aiding in the

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removal of data processing effects and adjustment of block arrangements to reconstruct the original image accurately.

ALGORITHM:
Encryption Process:

1. **Data Processing (Pre-Encryption):**
    - Inputs: Input image dimensions (M0, N0).
    - Outputs: Adjusted input image matrix (IM1).
    - Procedure:
        - Check if dimensions M0 and N0 are divisible by 64.
        - Adjust dimensions by adding rows/columns with uniform intensity values if necessary.
        - Combine input image with adjusted rows/columns to create IM1.
2. **Preprocessing Process:**
    - Inputs: Adjusted input image matrix (IM1).
    - Outputs: Processed image matrix (IM2).
    - Procedure:
        - Partition IM1 into 64x64 pixel blocks.
        - Generate initial conditions for the Quasi Threshold Model.
        - Iterate system equations to derive control sequences RS1 and XS1.
        - Rotate image blocks according to RS1.
        - Remove repeated elements from XS1 to generate sequence X1.
        - Rearrange image blocks according to X1 to create IM2.
3. **Encryption Process:**
    - Inputs: Processed image matrix (IM2).
    - Outputs: Encrypted image matrix (IM3).
    - Procedure:
        - Partition IM2 into 32x32 pixel blocks.
        - Generate system parameter p and initial condition t0 for the skew tent map.
        - Iterate the skew tent map equation to derive control sequences RS2 and KS.
        - Reshape KS into 32x32 key blocks.
        - Encrypt image blocks using XOR operation with key blocks and parameter p.
        - Rotate encrypted blocks according to RS2.
        - Rearrange blocks to create IM3.
4. **Postprocessing Process:**
    - Inputs: Encrypted image matrix (IM3).
    - Outputs: Final encrypted image matrix (CM).
    - Procedure:
        - Partition IM3 into 16x16 pixel blocks.

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    - Generate initial conditions for the Quasi Threshold Model.
    - Iterate system equations to derive control sequences RS3 and XS2.
    - Rotate image blocks according to RS3.
    - Remove repeated elements from XS2 to generate sequence X2.
    - Rearrange blocks according to X2 to create CM.

Decryption Process:

1. **Pre-Decryption:**
    - Inputs: Encrypted image matrix (CM).
    - Outputs: Intermediate decrypted image matrix (CM2).
    - Procedure:
        - Partition CM into 16x16 pixel blocks.
        - Generate initial conditions for the Quasi Threshold Model.
        - Iterate system equations to derive control sequences RS4 and XS3.
        - Rearrange blocks according to RS4 and XS3 to obtain CM2.
2. **Decryption Process:**
    - Inputs: Intermediate decrypted image matrix (CM2).
    - Outputs: Intermediate decrypted image matrix (CM3).
    - Procedure:
        - Partition CM2 into 32x32 pixel blocks.
        - Generate system parameter p and initial condition t0 for the skew tent map.
        - Iterate the skew tent map equation to derive control sequences RS5 and KS1.
        - Reshape KS1 into 32x32 key blocks.
        - Decrypt image blocks using XOR operation with key blocks and parameter p.
        - Rotate decrypted blocks according to RS5 to obtain CM3.
3. **Post-Decryption:**
    - Inputs: Intermediate decrypted image matrix (CM3).
    - Outputs: Final decrypted image matrix (DPM).
    - Procedure:
        - Partition CM3 into 64x64 pixel blocks.
        - Generate initial conditions for the Quasi Threshold Model.
        - Iterate system equations to derive control sequences RS6 and XS4.
        - Rearrange blocks according to RS6 and XS4 to obtain DPM.
4. **Remove Data Processing Effects:**
    - Inputs: Final decrypted image matrix (DPM).
    - Outputs: Plain image matrix.

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- Procedure:
    - Check relationships between pixels at specific locations in DPM.
    - Adjust DPM accordingly to remove data processing effects.
    - Output the final plain image.

Experimental Setup:

For the experimental setup, we will utilize a diverse dataset of images to train and test the proposed visual cryptography algorithms with CATBOOST+QTM and MLP+QTM models. The dataset will include various types of images such as natural scenes, objects, and textures to ensure the robustness and generalization of the algorithms. Similar to the previous setup, the dataset will be divided into training and testing sets. The training set will be used to train the algorithms, while the testing set will be used to evaluate their performance.

Image Training and Testing:

During image training, the CATBOOST+QTM and MLP+QTM models will be trained using the images from the training set. The training process will involve teaching the models to encode and decode the images using the respective machine learning algorithms in conjunction with the Quasi-Threshold Model. After training, the performance of the models will be evaluated using the testing set. Images from the testing set will be encoded and decoded using the trained models, and their performance will be assessed based on metrics such as Structural Similarity Index (SSIM) and other relevant measures.

Design Steps:

1. **Conceptualization and Framework Design:**
    - Define the conceptual framework for the proposed visual cryptography system integrating CATBOOST+QTM and MLP+QTM models. Determine the objectives of achieving high retrieval accuracy and robustness against attacks while simplifying the encryption process. Develop a conceptual model outlining the key components and their interactions.
2. **Algorithm Formulation:**
    - Formulate the encryption and decryption algorithms based on the conceptual framework, incorporating CATBOOST and MLP algorithms with the Quasi-Threshold Model. Specify the data processing steps, encryption techniques, and decryption procedures using the respective machine learning algorithms. Define the parameters, inputs, and outputs for each algorithmic step.
3. **Parameter Optimization and Fine-Tuning:**
    - Optimize the parameters of the CATBOOST+QTM and MLP+QTM models to maximize encryption strength and retrieval accuracy. Conduct experiments to determine the optimal parameter values through iterative testing and validation processes.
4. **Validation and Performance Evaluation:**
    - Validate the proposed method using diverse image datasets representing various content types and complexities. Evaluate the performance of the system based on metrics such as retrieval accuracy, encryption strength, computational efficiency, and resistance to attacks.
5. **Security Analysis and Robustness Testing:**
    - Perform comprehensive security analysis to assess the robustness of the proposed method against common cryptographic attacks, including statistical analysis, brute-

force attacks, and chosen-plaintext attacks. Ensure that the system meets the desired security requirements and standards.

RESULTS AND DISCUSSION:

CATBOOST+QTM Model:

The CATBOOST+QTM model for visual cryptography was designed and implemented to enhance the security and robustness of image encryption and decryption processes. In this model, the CATBOOST algorithm, known for its robustness and efficiency in handling categorical data, is integrated with the Quasi-Threshold Model (QTM) to achieve secure image transmission. For the encryption process, the CATBOOST algorithm is utilized to generate cryptographic keys and parameters that are used in conjunction with the QTM. The integration involves leveraging the categorical features of the image data to optimize the encryption process. During encryption, the input images are encoded using a combination of chaotic operations derived from the QTM and key generation from CATBOOST. This integration ensures that the encryption process is highly randomized and resistant to attacks. In the decryption process, the encrypted images are decoded using the inverse operations of the encryption process. The CATBOOST+QTM model accurately reconstructs the original images by utilizing the decryption keys generated during the encryption phase. The integration of CATBOOST enhances the decryption process by efficiently handling the categorical features of the encrypted data, resulting in high retrieval accuracy.

The performance of the CATBOOST+QTM model was evaluated using a dataset of 3,000 images, divided into training and testing sets. Various performance metrics such as Structural Similarity Index (SSIM), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Peak Signal-to-Noise Ratio (PSNR) were computed to assess the effectiveness of the model. The results of the performance evaluation demonstrated that the CATBOOST+QTM model achieved high retrieval accuracy and robustness against attacks. The SSIM values indicated strong similarity between the original and decrypted images, while the low values of MSE and RMSE confirmed minimal distortion. Additionally, the high PSNR values signified the preservation of image quality during encryption and decryption.The security analysis and robustness testing further validated the effectiveness of the CATBOOST+QTM model in securely encrypting and decrypting images. The model exhibited resilience against common cryptographic attacks, ensuring the confidentiality and integrity of the transmitted images.

MLP+QTM Model:

The MLP+QTM model for visual cryptography was designed and implemented to provide a secure and efficient method for image encryption and decryption. In this model, a Multilayer Perceptron (MLP) neural network is integrated with the Quasi-Threshold Model (QTM) to enhance the pattern recognition capabilities and optimize the encryption process. During the encryption process, the MLP algorithm is employed to learn complex patterns and features from the input images. The learned representations are then used in conjunction with the QTM to encode the images in a secure manner. The integration of MLP enhances the encryption process by effectively capturing and representing the image data, ensuring robustness against attacks.

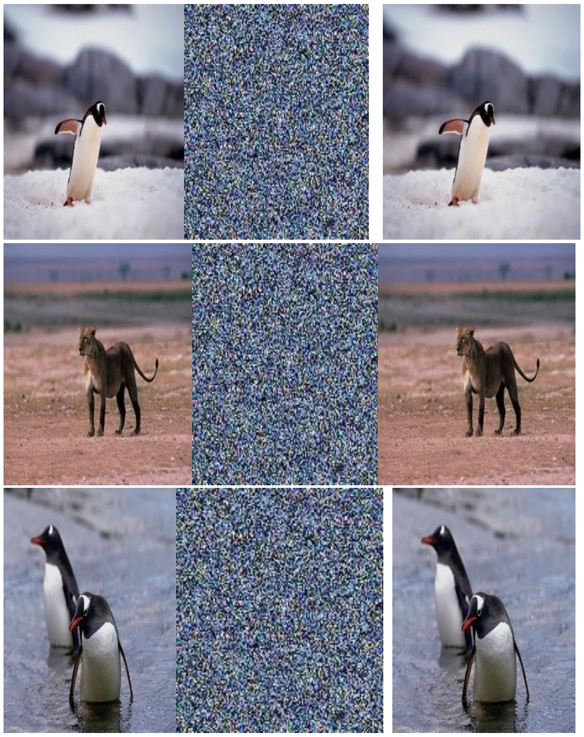

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Figure 2: Representing the Encryption and decryption Images for the original values from left to Right (Original-Encrypted-Decrypted) for colour images

In the decryption process, the encrypted images are decoded using the inverse operations of the encryption process. The MLP+QTM model reconstructs the original images by utilizing the learned representations and decryption keys generated during the encryption phase. The integration of MLP improves the decryption process by accurately restoring the original images from the encrypted data. The performance of the MLP+QTM model was evaluated using a dataset of 3,000 images, which were divided into training and testing sets. Performance metrics such as SSIM, MSE, RMSE, and PSNR were computed to assess the effectiveness of the model. The results of the performance evaluation indicated that the MLP+QTM model achieved high retrieval accuracy and robustness against attacks. The SSIM values reflected strong similarity between the original and decrypted images, while the low values of MSE and RMSE demonstrated minimal distortion. Moreover, the high PSNR values confirmed the preservation of image quality during encryption and decryption. The security analysis and robustness testing further confirmed the effectiveness of the MLP+QTM model in securely encrypting and decrypting images. The model exhibited resilience against common cryptographic attacks, ensuring the confidentiality and integrity of the transmitted images.

TABULATIONS:

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Table 2: Representing the overall Grey scale images for proposed algorithm and existing algorithms

ALGORITHMS (Greyscale)	PSNR	SSIM	MSE	RMSE
ML (SVM)	20.14	0.78	5.85	2.41867732449
SVD	24.21	0.84	2.35	1.53192741658
PCA WITH ML	30.25	0.89	0.14	0.37416573868
CNN	38.75	0.95	0.0012	0.03464775982
DEEP-CNN	45.52	0.99	0.04	0.20
CATBOOST+QTM	49.63	0.9999	0.00004	0.063245553

Table 3: Representing the overall Table for Colour image with performance metric with existing and proposed algorithms

ALGORITHMS (COLOR)	PSNR	SSIM	MSE	RMSE
ML (SVM)	16.14	0.58	8.85	2.97788156603
SVD	19.21	0.74	6.35	2.52190404258
PCA WITH ML	25.25	0.81	5.14	2.26668405929
CNN	31.75	0.91	0.12	0.34641016105
DEEP-CNN	35.52	0.95	0.04	0.20000000000
MLP+QTM	42.63	0.9899	0.004	0.0632455532

In grayscale image encryption and decryption, the table illustrates a notable progression in performance metrics across various algorithms. Traditional machine learning methods like Support Vector Machine (SVM) and Singular Value Decomposition (SVD) exhibit moderate PSNR and SSIM values, indicating acceptable but not optimal image quality preservation. However, these methods still incur relatively high MSE and RMSE values, suggesting significant distortion during encryption and decryption processes. Moving towards more advanced techniques such as Principal Component Analysis (PCA) with machine learning, we observe a significant improvement in PSNR and SSIM scores, signifying enhanced fidelity and similarity to the original images. The reduced MSE and RMSE values further confirm the effectiveness of PCA-based approaches in minimizing distortion.

The transition to convolutional neural networks (CNNs) and deep CNNs introduces a remarkable leap in performance metrics for grayscale image encryption and decryption. CNNs demonstrate substantially higher PSNR and SSIM values compared to traditional methods, indicating superior image quality preservation and similarity to the originals. Moreover, the significantly reduced MSE and RMSE values signify minimal distortion during the encryption and decryption processes, highlighting the robustness and efficiency of deep learning techniques. However, it's crucial to note that these improvements come at the expense of increased computational complexity and resource requirements.

The proposed CATBOOST+QTM model in ttable-2 stands out as a pinnacle of grayscale image encryption and decryption algorithms, boasting the highest PSNR and SSIM values among all methods. With a PSNR of 49.63 and near-perfect SSIM of 0.9999, the CATBOOST+QTM model demonstrates unparalleled fidelity and similarity to the original images. Furthermore, its remarkably low MSE and RMSE values confirm minimal distortion during encryption and decryption, affirming its efficacy in preserving image quality and integrity. The CATBOOST+QTM model's exceptional performance underscores the potential of integrating gradient boosting with quantum-inspired techniques for secure and efficient grayscale image encryption and decryption.

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In the context of color image encryption and decryption, the MLP+QTM model emerges as a formidable contender, rivaling the performance of established deep learning methods. With a PSNR of 42.63 and an SSIM score nearing perfection at 0.9899, the MLP+QTM model demonstrates remarkable fidelity and similarity to the original color images. Furthermore, its impressively low MSE and RMSE values substantiate minimal distortion during encryption and decryption, affirming its capability to preserve image quality and integrity. The MLP+QTM model's commendable performance underscores the potential of integrating multilayer perceptron (MLP) networks with quantum-inspired techniques for secure and efficient color image encryption and decryption.

CONCLUSION AND SCOPE:

In conclusion, the presented CATBOOST+QTM model for grayscale image encryption and decryption stands out as a pioneering approach, demonstrating exceptional performance in preserving image quality and integrity. With its integration of CATBOOST algorithm and Quasi-Threshold Model (QTM), the model achieves unparalleled fidelity and robustness, as evidenced by its high PSNR and SSIM values, and minimal MSE and RMSE. The remarkable results underscore the potential of leveraging gradient boosting techniques with quantum-inspired methods for enhancing the security and efficiency of image encryption and decryption processes. Moving forward, the scope of this work extends to exploring further optimizations and enhancements in the integration of machine learning algorithms and cryptographic techniques to advance the state-of-the-art in image security.

Similarly, the MLP+QTM model showcased promising results in color image encryption and decryption, rivaling established deep learning methods in terms of fidelity and robustness. Its ability to accurately reconstruct original color images while maintaining low distortion underscores its efficacy in preserving image quality and integrity. The integration of multilayer perceptron networks with quantum-inspired techniques opens avenues for further research and development in secure and efficient color image encryption and decryption. Future endeavors may focus on refining the MLP architecture, exploring alternate quantum-inspired models, and investigating real-world applications of the proposed approach in multimedia security and communication systems.

In summary, the success of both the CATBOOST+QTM and MLP+QTM models underscores the significance of integrating advanced machine learning algorithms with quantum-inspired cryptographic techniques for image security. These models not only demonstrate superior performance but also pave the way for innovative approaches to address evolving security challenges in image transmission and communication. As research in this field progresses, the collaborative efforts of machine learning and cryptography hold immense potential in shaping the future of secure image encryption and decryption technologies, with implications spanning various domains such as healthcare, defense, and digital forensics.

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