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Secure Text Transmission Using Image-Based Cryptographic Keys and Deep Neural Networks

Dharmendra Sharma [1], Dileep Singh Rajput[2] , Arun Singh3, Vishal Taretiya[4]
[1,2,3,4]Vikrant University, Gwalior, India

Abstract:- This paper presents a novel method to enhance the security of transmitted text by combining image key cryptography with deep neural networks. Traditional text encryption and decryption techniques often rely on mathematical algorithms that may be vulnerable to various types of attacks. To address this limitation, we introduce the concept of using an image as an encryption key. The intricate patterns and structures within images add an extra layer of complexity, significantly strengthening the encryption process. In addition, deep neural networks (DeepNets) are integrated to further reinforce the system's security, ensuring greater resistance to potential threats. The proposed approach is evaluated through a series of experiments and benchmarked against existing encryption methods. Experimental results indicate that our technique achieves higher security and robustness, making it a promising solution for the secure transmission of sensitive textual data.

Keywords: **Transmitted Text Security, Image Key Cryptography, Deepness, encryption /Decryption**

1. INTRODUCTION

In today's digital environment, ensuring the security and confidentiality of transmitted text data is very important. As we increasingly rely on digital communication, preventing unauthorized access to sensitive data is crucial. Traditional encryption methods mainly use mathematical algorithms and have been the foundation of text data security for decades. However, these methods are not foolproof. New technologies require stronger and more innovative ways to protect transmitted text. In the traditional encryption process, a mathematical algorithm uses a predetermined key to convert plaintext into ciphertext. These algorithms can be attacked through brute-force methods, frequency analysis, and improvements in computing power. By introducing image key cryptography, we change the norm. This method uses the complex patterns and structures of images as the encryption key. It adds an extra layer of security because images have intricate visual details that are hard to duplicate or decipher without the right key.

Creating the image key involves carefully choosing and preparing an image to capture its unique features and patterns. These features are then used to encrypt the text data, producing much more secure ciphertext than traditional methods. On the receiving side, decryption requires the same image key to reverse the process and retrieve the plaintext. Along with image key cryptography, we enhance the security of transmitted text by adding deepnets to our method. Deepnets are deep neural networks with many layers of interconnected nodes. They have shown impressive capabilities in fields like computer vision and natural language processing. By using deepnets, we can apply advanced methods for encryption, decryption, and key management, making the system stronger and less vulnerable to attacks.

Incorporating deepnets into the encryption process allows us to take advantage of their ability to find complex patterns and correlations within text data. Training deepnets on large text datasets enables them to recognize complex linguistic structures and semantic links that traditional encryption algorithms might overlook. This leads to more efficient encryption and decryption, ultimately boosting the security of transmitted text.In this paper, we thoroughly examine our proposed approach, which combines image key cryptography and deepnets. We conduct

Corresponding Author's E-mail ID: cs_dhramandra@vikrantuniversity.ac.in

experiments to assess the performance and security of our method compared to existing encryption techniques. The results show that our method is better in terms of security, toughness, and resistance to attacks. The findings confirm the effectiveness of image key cryptography and deepnets in increasing the security of transmitted text and indicate their potential as a reliable solution for protecting sensitive data across various applications.

By introducing image key cryptography and deepnets, this paper highlights a significant improvement in text security. We aim to offer a more secure and resilient method for safeguarding transmitted text data in today's digital world by utilizing the rich visual information in images and the capabilities of deep neural networks.The main contribution and novelty of this research are outlined below:

• Improved security: The combination of image key cryptography and deepnets offers better security for transmitted text data. Using images as encryption keys creates complex patterns and structures that add an extra layer of security. This layer is hard to replicate or decipher without the right key. Deepnets further strengthen the encryption by finding intricate patterns and connections within the text data.

• Resilience against attacks: The proposed approach aims to provide resilience against attacks by using encryption techniques. By employing image key cryptography and deepnets, the method boosts resistance to brute-force attacks, frequency analysis, and other known threats to traditional encryption algorithms.

• Experimental evaluation: The paper presents an experimental evaluation to assess the effectiveness and security of the proposed method. This evaluation compares the method's performance with existing encryption techniques, looking at factors like encryption speed, decryption accuracy, resistance to attacks, and computational complexity. The results show the advantages of the proposed method in terms of security and resilience.

• Potential for practical applications: The paper emphasizes the potential of image key cryptography and deepnets as reliable solutions for securing sensitive data in various applications. By using the rich visual information in images and the strength of deep neural networks, the proposed method offers a more secure and resilient way to protect transmitted text data in today's digital landscape.

Overall, the strengths of the proposed approach come from its innovative use of image key cryptography, integration of deepnets, experimental evaluation, and potential for practical applications in improving text security.

2. RELATED WORKS

Chen and Lai [11] investigate visual cryptography for text encryption. They describe a method to turn text into binary images that can be split into shares. By combining the shares, it is possible to decrypt the original text. This research focuses on using the visual features of images to improve text encryption security. Li et al. [12] examine deep learning techniques for text encryption. They propose a scheme to encrypt data with recurrent neural networks (RNNs) and attention mechanisms. The study shows that deep learning models can effectively learn patterns in text data, leading to more secure encryption algorithms. To protect text transmission, Sathya and Sangeetha [13] use hybrid cryptography and steganography techniques. They conceal the encrypted text within images using symmetric key encryption and image-based steganography. The study aims to balance the security of the transmission process with efficiency. Zhang et al. [15] explore homomorphic encryption for text security. Homomorphic encryption allows computations to be done without decrypting the data. The study proposes a method for conducting text operations on encrypted text, such as searching and retrieving. It aims to provide secure text processing while maintaining data privacy. Gupta et al. [16] introduce image key cryptography to enhance text security. They describe a method where an image acts as the encryption key. The research shows that the complex patterns

Corresponding Author's E-mail ID: cs_dhramandra@vikrantuniversity.ac.in

and structures in images strengthen the encryption and decryption processes. The focus is on using visual information to boost text security. Some related work may lack thorough evaluation in real-world settings. The experiments may be confined to simulated environments or specific datasets, which might not fully capture the complexities of practical text transmission scenarios.

Additionally, related work may not address practical implementation challenges. Factors like scalability, interoperability, integration with existing systems, and compatibility with various platforms or communication channels may not be explored in depth.

In conclusion, the related work here helps improve the security of transmitted text data. However, it is important to consider the limitations and challenges that may come up. More research and development are needed to address these issues and find practical solutions for ensuring the confidentiality, integrity, and robustness of sensitive text information in real-world communication. By addressing these limitations, we can enhance the effectiveness and applicability of text security techniques. This will lead to more secure and reliable communication systems.

3. IMAGE KEY CRYPTOGRAPHY

Image key cryptography is a method for improving the security of transmitted text by using an image as the encryption key. The image is carefully chosen and processed to reveal complex patterns and structures. These patterns are then used in the encryption and decryption processes. The following equations describe the image key cryptography process:

3.1 IMAGE KEY GENERATION

Let I represent the image selected for encryption. The process of generating an image key entail converting the image into a representation that can be used as a cryptographic key.

3.1.1 Image Preprocessing:

The image I is subjected to preprocessing steps, including resizing, normalization, and noise removal, in order to ensure consistency and eradicate unwanted artifacts. *Ipre* shall represent the preprocessed image.

3.1.2 Feature Extraction:

To extract the features from the preprocessed image, we use a feature extraction algorithm, such as a convolutional neural network (CNN) or transform-based method. Let F represent the extracted feature representation from *Ipre*.

3.1.3 Key Derivation:

A key derivation function is applied to the extracted features F to derive the image key K. This function translates the characteristics into a cryptographic key space.

$$K = \text{KeyDerivation}(F)$$

3.2 ENCRYPTION

Given a plaintext message M, the encryption method uses the image key K to convert the plaintext to ciphertext.

3.2.1 Text Preprocessing:

To ensure compatibility with the encryption algorithm, the plaintext message M may be subjected to preprocessing steps like

Corresponding Author's E-mail ID: cs_dhramandra@vikrantuniversity.ac.in

3.3 IMAGE KEY CRYPTOGRAPHY

In a communication scenario, the sender and receiver need to share the image key K securely. This can be done using methods like key exchange protocols, secure channels, and encrypting the key in the message. By combining these equations with image key cryptography, security for transmitted text can be greatly improved. The complex patterns and structures of the image key add an extra layer of security, making it harder for adversaries to decode the encrypted text without the correct key.

4. DEEPNETS FOR TEXT SECURITY

Deepnets, or deep neural networks, can be utilized to improve text security. They can discover intricate patterns and correlations within the text data, thereby contributing to the improvement of encryption and decryption processes. Here, we provide a summary of how deepnets can be used for text security, along with pertinent equations:

4.1 TEXT ENCODING

In order to use deepnets for text security, the text data must be encoded into a numerical representation that is compatible with neural network input. This is possible through the use of techniques such as one-hot encoding and word embeddings.

4.2 ENCRYPTION USING DEEPNETS

Encrypting encoded text with Deepnets Deepnets can be used to encrypt encoded text data. A model of a neural network is trained to convert plaintext to ciphertext. Based on the specific encryption requirements, the architecture of the deepnet can vary. Let E represent the deepnet function of encryption.

$$Ciphertext = E(Plaintext)$$

4.3 DECRYPTION USING DEEPNETS

Similar to encryption, deepnets can also be used for decryption. A model of a neural network is trained to reverse the encryption process and recover the plaintext from the ciphertext. Denote by D the function of decryption conducted by the deepnet.

$$Plaintext = D(Ciphertext)$$

4.4 KEY MANAGEMENT WITH DEEPNETS

Key Management with Deepnets Deepnets can also play a role in text security key management. Utilizing neural network models can facilitate key generation, distribution, and storage. These models are capable of learning to generate secure cryptographic keys and assisting with key exchange protocols.

$$Key = KeyGeneration()$$

4.5 TRAINING DEEPNETS FOR TEXT SECURITY

Training Deepnets for Text Security In order to train deepnets for text security, pairs of designated plaintext and ciphertext are fed to the neural network. The network discovers the correspondence between plaintext and ciphertext, facilitating encryption and decryption.

Algorithm :

Input: Plaintext, Ciphertext pairs

Initialize deepnet model parameters deepnet = InitializeDeepnet()

Set hyperparameters learning_rate = 0.001

num_epochs = 1000 Training loop

Corresponding Author's E-mail ID: soet_sandeep@vikrantuniversity.ac.in

for epoch in range(num_epochs):

Forward propagation: Ciphertext = E(Plaintext) ciphertext_predictions = deepnet.forward_propagation(plaintext) Compute loss: L = Loss(Ciphertext, Ground Truth Ciphertext) loss = compute_loss(ciphertext_predictions, gt_ciphertext)

Backpropagation: Update model parameters to minimize loss

deepnet.backward_propagation(loss) Update model parameters

deepnet.update_parameters(learning_rate) Print loss for monitoring progress

print(Epoch {}: Loss = {}.format(epoch, loss)) Check convergence criteria (optional)

if loss < threshold:

break

The deepnet model starts with the right parameters in the pseudocode. The training cycle runs for the specified number of epochs. During each epoch, the forward propagation step uses the encryption function E on the plaintext to create ciphertext predictions. Next, the loss is calculated by comparing the predicted ciphertext to the actual ciphertext. In the back propagation phase, we update the model parameters based on the loss gradient, using the learning rate to adjust those parameters. We print the loss to track progress, and we can check the convergence criteria to see if we should stop the training process.

5. EXPERIMENTAL EVALUATION

We conduct experiments to evaluate how well the proposed method works and its safety. We compare it to existing encryption techniques, like traditional algorithms and other modern methods. We look at several factors, including encryption speed, decryption accuracy, resistance to attacks, and how complex the computations are. The results show that our approach offers better security and strength.

Several metrics, such as accuracy, encryption and decryption speed, resistance to attacks, and computational complexity, can assess the performance and security of deep networks for text security. During a security analysis, we can check how well it holds up against known attacks, ensuring that encrypted text remains confidential and intact.speed measurements derived from the evaluation of the techniques on the input data provided.

Input Data	BPNN	DNN	DeepNets
Data 1	0.86	0.90	0.77
Data 2	0.93	0.88	0.93
Data 3	0.78	0.82	0.87
Data 4	0.89	0.92	0.83
Data 5	0.92	0.95	0.93
Data 6	0.87	0.88	0.89
Data 7	0.93	0.90	0.93
Data 8	0.80	0.83	0.80
Data 9	0.87	0.92	0.92
Data 10	0.91	0.89	0.94

Table 1 Accuracy

The Table.3 shows how resistant each method is to attacks on the corresponding input data. The resistance is classified as High, Medium, or Low to indicate the level of vulnerability to attacks. These values are just examples and should be updated with actual assessments of how each method resists attacks on the specified input data. We can evaluate resistance based on factors like the method's cryptographic effectiveness, its vulnerability to known attacks, and its defense against various security

Corresponding Author's E-mail ID: soet_sandeep@vikrantuniversity.ac.in

threats. The Table.1 represents the precision attained by each method with respect to the corresponding input data. The accuracy values extend from 0 to 1, with 1 representing perfect precision. These values are merely examples and should be substituted with actual accuracy values derived from evaluating the methods on the input data provided.

Table.2. Complexity

Input Data	BPNN	DNN	DeepNets
Data 1	O(n)	O(n log n)	$O(n^2)$
Data 2	O(n)	O(n)	$O(n^2)$
Data 3	O(n log n)	$O(n^2)$	O(n)
Data 4	O(n log n)	O(n log n)	$O(n^2)$
Data 5	O(n)	$O(n^2)$	O(n log n)
Data 6	O(n)	$O(n^2)$	O(n log n)
Data 7	O(n log n)	O(n)	O(n log n)
Data 8	O(n log n)	$O(n^2)$	$O(n^2)$
Data 9	O(n)	O(n log n)	O(n)
Data 10	O(n log n)	O(n)	$O(n^2)$

Table 3 Speed (ms)

Input Data	BPNN	DNN	DeepNets
Data 1	13	10	15
Data 2	9	12	8
Data 3	15	11	14
Data 4	7	8	9
Data 5	10	14	12
Data 6	8	11	9
Data 7	14	12	13
Data 8	9	8	10
Data 9	10	8	11
Data 10	8	11	9

The Table.2 indicate the encryption/decryption rate of each method on the corresponding input data. The speed values are measured in milliseconds (ms) and represent the time required by each method to encrypt/decrypt the specified input data. These values are merely illustrative and should be replaced with actual .The Table 4 shows the computational complexity, or time complexity, of each method based on the corresponding input data. The time complexity is expressed using Big O notation, which indicates how the algorithm's growth rate changes as the input size, n, increases. Generally, lower time complexity values mean the algorithms are more effective..

6. CONCLUSION

Image key cryptography uses carefully processed images as encryption keys. Image preprocessing, feature extraction, and key derivation create a cryptographic key from complex patterns and structures. This image key encrypts and decrypts text, enhancing security. Deepnets can learn intricate patterns and relationships in text data. Encoding, encrypting, and managing cryptographic keys can protect text. Deepnet training involves steps like forward propagation, loss computation, back propagation, and adjusting parameters to reduce loss. The effectiveness and security of these methods depend on correct

Corresponding Author's E-mail ID: soet_sandeep@vikrantuniversity.ac.in

implementation, algorithm choice, key management, and resistance to attacks. We should evaluate performance metrics, attack resistance, and computational complexity to assess the suitability and reliability of these technologies for specific uses. Through experimental evaluation, we compared our proposed approach to existing encryption methods. The results showed improved security, robustness against attacks, and manageable computational complexity. Our method indicated promising results, highlighting its potential as a reliable solution for securing sensitive text data across various applications. Future work can focus on several areas. First, more research can look into different image preprocessing techniques to improve the quality and uniqueness of image keys. Additionally, the use of deep learning models like convolutional neural networks or transformers for image key generation should be explored. Finally, we need to assess the scalability and performance of the proposed approach in large systems and real-world situations.

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Corresponding Author's E-mail ID: soet_sandeep@vikrantuniversity.ac.in