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STEGOCRYPTNET: A DEEP LEARNING AND NTRU-BASED CRYPTOGRAPHIC IMAGE STEGANOGRAPHY FRAMEWORK

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ABSTRACT

In present digital age, protecting and safeguarding essential information against unauthorized access is considered crucial. Thus, image steganography is regarded as they offer strong approach fo concealing the secret data within images, allowing secure communication. Henceforth, this paper focuses on developing a SecureNet-Stego method for achieving improved image steganography process by integrating Deep Learning (DL) model with advanced cryptographic techniques. The proposed model is developed using Discrete Wavelet Transform (DWT) for attaining optimized frequency domain embedding while enhancing both imperceptibility and robustness. To further attain increased security, N^{th} degree polynomial Ring Unit (NTRU) based encryption algorithm, a post-quantum cryptographic technique which encrypts the secret image prior to embedding to protect it against cryptanalysis attacks. Moreover, SecureNet-Stego model is deployed using a morphological Transformer based Generative Adversarial Network (GAN) for achieving precise and accurate encoding and extraction of secret image. The proposed system is implemented using python software and the obtained results showcases improved steganography capacity, resilience and enhanced security and reliability, leading to highly efficient performance with secure digital communication.



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I. INTRODUCTION

The growing developments of Information technologies led to the need for protecting the data privacy, security and confidentiality [1], [2]. Thus, hiding the original data approaches are regarded for supporting secured data transmission. There are various information protecting techniques at present as listed in Fig. 1, which are mainly divided into three major categories that is, cryptography, steganography and digital watermarking [3-5]. To be more specific, cryptography is the process of converting plain text to cipher text, whereas, digital watermarking is the process of inserting hidden information within the transmitting data [6], [7]. While, image steganography refers to process of hiding secret information inside an image [8], [9]. The major aim behind the development of image steganography is to protect the data by concealing secret important data in a cover image for secured communication, by this means only receiver is capable of accessing secret message from stego-image [10], [11]. Significantly, stego-image should be identical to original image visibly and discriminately in order to avoid being discovered. Henceforth, image steganography has intrigued lot of attention towards itself, resulting in constant research, enhancement and advantages [12].

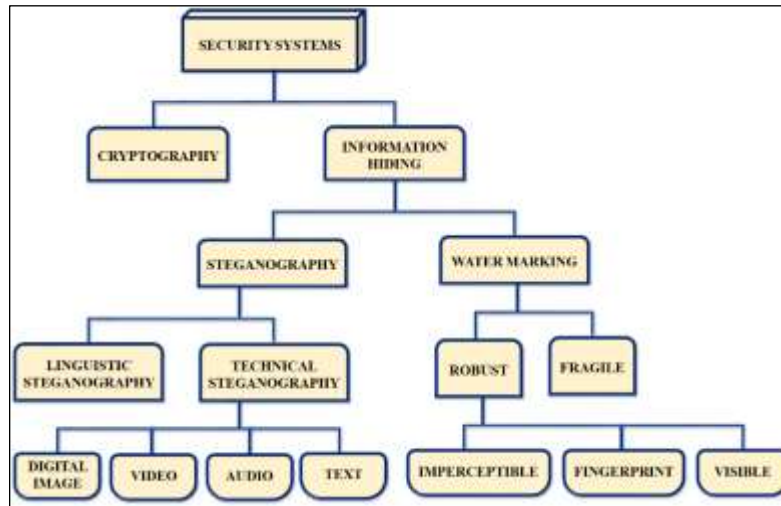


Figure 1: Information protection approaches.

Source: Authors, (2026).

Recently, various steganography approaches are developed to further enhance the data security and privacy. Traditionally, image steganography is performed using Least Significant Bits (LSB) [13], which is a substitution method. LSB generally, an encoding based steganography in which the least significant bit is overwritten using the secret messages, LSB's are simple and easy to implement, leading to unnoticeable variations to the cover image, but this approach is prone to easy detection as they contain predictable patterns in terms of alterations, resulting in weak security and data privacy [14]. Therefore, secret image need to be covered in such a way that it cannot be easily cracked. Thus, various deep learning approaches are presently drawing more attention as they are considered as a strong technology in several aspects [15]. The authors in [16] developed Artificial Neural Network (ANN) based image steganography process for attaining effective encryption. The deployment of ANN provides enhanced invisibility of the secret image, with increased adaptability towards varying image types and sizes along with improved ability to handle complex image patterns. However, ANN requires complex training and struggles with overfitting issues. Significantly, in [17], the authors utilized Deep Neural Network (DNN) along with gradient based filter technique to further enhance DNN model. This topology provides better feature extraction with more precise predictions by integrating varying filtering techniques, enabling to adjust the network's weight on the basis of the gradient information, thereby, allowing to handle complex data patterns. Nevertheless, increased model complexity with higher computational requirements, leading to increased training period and resource needs, thus, limiting the scalability for larger dataset. Consecutively, Recurrent Neural Network (RNN) steganography technique is developed in [18] which enables efficient embedding and extracting of hidden features within the provided dataset, enhancing RNN's ability to attain temporal dependencies and patterns. Utilizing RNN effectively enhances the data security and privacy with increased robustness while maintaining the integrity of the cover image and allowing increased concealing of the secret image in highly protected manner. Despite these advantages, RNN is prone to various difficulties including higher training duration, cannot handle noise and interferences within the dataset. In addition to this, RNN suffers from increased sensitivity in terms of hyper-parameter tuning which leads to increased overfitting problems. Furthermore, the authors in [19] introduced Convolutional Neural Network (CNN) with Discrete Cosine Transform (DCT) which combines the benefits of both CNN and DCT, enabling highly effective and secure data hiding within images. In this approach, author utilized two-step process namely feature extraction and selection to achieve data embedding with reduced visual distortion. However, this topology is still prone to various difficulties including reduced image quality while embedding larger datasets, increased computational complexity. Therefore, overcome and prevail over the above stated shortcomings and limitations this paper proposes a morphological transformer based GAN steganography method using DWT module and NTRU based encryption and decryption approach. This approach achieves improved data embedding with the help of DWT which enhances the image quality, whereas, morphological transformer based GAN attains enhanced feature extraction. Additionally, the implementation of NTRU assures highly increased security, making the hidden data tough to detect and enable robust protection towards unauthorized access. The major objectives and outlines of the proposed model is listed in the following,

- To implement an improved image steganography technique by integrating DL and Cryptographic approaches for increased data security.
- To attain optimized frequency-domain embedding, DWT is deployed which enables better concealing of data, thereby reducing the perceptible within the cover image.
- To implement NTRU based encryption for enabling increased secure and robust cryptographic approach, leading to improved system resilience towards unauthorized access.
- To utilize a morphological transformer based GAN to attain precise encoding and extraction of secret image while maintaining the image quality.

II. PROPOSED METHODOLOGY

Proposed system block diagram is shown in Fig. 1 , developed to attain secure image steganography by utilizing DWT, NTRU and morphological transform based GAN approach. The process begins with the input image which undergoes multi-stage process including DWT, encryption and GAN based extraction and decryption to assure data security and privacy.

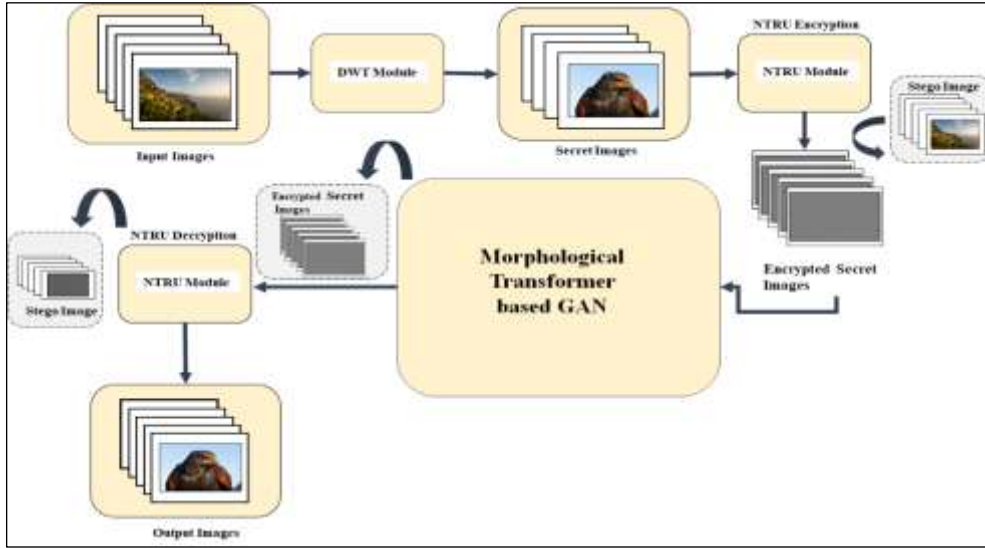


Figure 2: Proposed System Block Diagram.
Source: Authors, (2026).

Initially, the input is taken which acts as cover image for embedding secret image. After which, these input images are passed to DWT module, where the input images undergo DWT to attain optimized frequency domain embedding, thereby facilitating effective data hiding. Later, the secret image is given to the NTRU module for cryptographic process where encryption is performed to improve the data security against unauthorized access. Now, the output from the NTRU module, which is the encrypted stego image that contains the hidden secret image. This encrypted image is then fed into the morphological transformer based GAN to achieve robust data handling and extraction, which reconstructs the secret image without causing any significant loss to data. Now, the encrypted secret image is further passed to NTRU based decryption module, which enables to retrieve original secret image from stego image, thus, restoring original image. Therefore, by implementing the proposed techniques, this system assures highly secured and protected image steganography process with increased adaptability, robustness, imperceptibility and reliability.

II.1 MODELLING OF DWT MODULE

DWT is commonly known as transform domain technique that comprises of two types of operations namely, scaling and wavelet. DWT is utilized for converting signals from spatial domain to frequency domain. For image processing, DWT converts image pixels into frequency coefficient, this conversion assures increased imperceptibility and robustness. The 2D-DWT signal is acquired using the 1D wavelet transform specifically on image's row and columns. The scaling function of 2D-DWT is calculated using,

$$s(x, y) = s(x) s(y) \quad (1)$$

Where, $s(x)$ indicates the 1D scaling function used on the images along the horizontal and vertical axes. Significantly, the wavelet function for three sub-bands is represented using,

$$W_{hl}(x, y) = s(x)w(y) \quad (2)$$

$$W_{vl}(x, y) = w(x)s(y) \quad (3)$$

$$W_{dl}(x, y) = w(x)s(y) \quad (4)$$

Where, $W_{hl}(x, y)$, $W_{vl}(x, y)$ and $W_{dl}(x, y)$ represents the horizontal, vertical and diagonal wavelets. DWT divides an image into four different sub-bands of equal size, where each sub-band consist of different frequency components, which is known as 2D-DWT decomposition. This process is carried on using low-pass and high pass filters, where both filters operates on scaling and wavelet functions. The major benefit of using DWT-based approach is that, this approach separates images into low, middle and high frequency sub-bands while maintaining edge information without interfering other frequency components. During the first level of 2D-DWT, the given image is divided into four sub-bands namely, LL (low-low): Indicates approximation of image, LH (low-high) indicates the horizontal aspects, HL (high-low) indicates vertical aspects and HH (high-high) indicates the diagonal aspects respectively. Significantly, the middle frequency bands are most commonly chosen for steganographic embedding process as these enable proper balance among the imperceptibility and robustness.

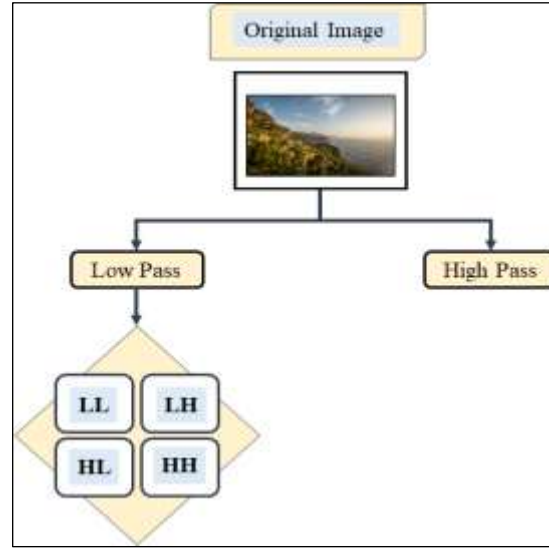


Figure 3: DWT.
Source: Authors, (2026).

In the proposed DWT based image steganography process, LH and HL bands are selected for embedding the secret image as these provide reduced visual distortion with increased robustness.

$$low(k) = \begin{cases} \frac{1}{\sqrt{2}}, k = 0; \\ \frac{1}{\sqrt{2}}, k = 1; \\ 0, otherwise. \end{cases} \quad (5)$$

$$High(k) = \begin{cases} \frac{1}{\sqrt{2}}, k = 0; \\ \frac{1}{\sqrt{2}}, k = 1; \\ 0, otherwise. \end{cases} \quad (6)$$

The wavelet filter is utilized in this decomposition due to its rapid and memory-effective ensuring improved embedding process while maintaining quality of image with highly secure hiding of secret data. Thus, by utilizing DWT based frequency domain embedding assures increased security in terms protect image transmission and data hiding. In addition to this, to assure highly protected data transmission, NTRU based cryptosystem is deployed for achieving optimum encryption method.

II.2 MODELLING OF NTRU MODULE

The cryptographic mechanism such as NTRU uses polynomial functions on a specific algebraic structure arising from the polynomial quotient rings or polynomial convolutional rings and the basic structure of NTRU cryptosystem is given in Fig. 3. NTRU is a lattice-based public key cryptosystem and NTRU functions based on the polynomial rings which is expressed as,

$$R_{N,t} = \frac{Z_t[X]}{(X^N - 1)} \quad (7)$$

Where, $Z_t[X]$ indicates set of polynomials with integer coefficient minimized module t and $(X^N - 1)$ implies the polynomial that is presently the standardized version to attain the modules of the polynomial arithmetic functions utilized by various cryptographic applications. 'a' is considered as polynomial in X defined using a set of integer coefficients a_i , here, i refers to the coefficient of a in degree i respectively, which depicted as,

$$a(x) = a_0 + a_1 \cdot x + a_2 \cdot x^2 + \dots + a_i \cdot x^i + \dots + a(N-1) \cdot x^{(N-1)} \quad (8)$$

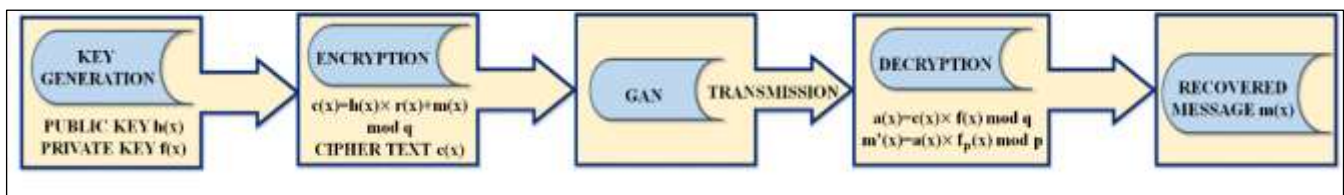


Figure 4: NTRU Cryptosystem.
Source: Authors, (2026).

Encryption and decryption operation is carried out using polynomial multiplication in NTRU based methods. The product of two polynomials, $c(x) = a(x) \times b(x)$, is other polynomial and their corresponding co-efficient is evaluated using,

$$C_k = \sum_{i+j=k \bmod N} (a_i \cdot b_j) \bmod t, \text{ for } i, j, k = 0, \dots, N-1 \quad (9)$$

The NTRU encryption is carried out using two truncated polynomial rings namely, $R_{N,q}$ and $R_{N,p}$, here, N denotes the prime number which is used to identify the degree of the truncated polynomials, ' q ' and ' p ' represents the co-prime where ' q ' is relatively larger than ' p '. In cryptosystem, NTRU encryption generally consists of three operations such as Key generation, encryption and decryption. The ternary polynomial are randomly selected during the key generation process. $f(x) \in R_{N,p}$ polynomial is invertible modulo p and modulo q . The two secret polynomial $f(x)$ and $g(x)$ is used for attaining the public key $h(x) \in R_{N,p}$ which is determined using,

$$h(x) = p \cdot f_q(x) \times g(x) \bmod q \quad (10)$$

Where, $f_q(x)$ is the inverse of $f(x)$ modulo q . The encryption operation is performed by encoding the message using the ternary polynomial $m(x)$ and a blinding polynomial $g(x) \in R_{N,p}$. The encrypted message $c(x)$ is attained using polynomial multiplication and addition, which is given by,

$$c(x) = h(x) \times r(x) + m(x) \bmod q \quad (11)$$

The decryption operation in NTRU cryptosystem is obtained by evaluating an intermediate polynomials, that is by multiplying the cipher text and the private key, which is calculated as,

$$a(x) = c(x) \times f(x) \bmod q \quad (12)$$

Which is further utilized for attaining the message m using,

$$m'(x) = a(x) \times f_p(x) \bmod p \quad (13)$$

In addition to this, Morphological Transformer based GAN is deployed for achieving enhanced security, robustness and reliability effective reconstruction of secret image without compromising the image quality and information.

II.3 MODELLING MORPHOLOGICAL TRANSFORMER BASED GAN

The morphological transformer based GAN for image steganography is the combination of transformer for feature extraction and morphological processing to attain enhanced concealing and embedding of secret images while maintaining their imperceptibility which is shown in Fig. 4. GAN have depicted higher potential in image steganography process by enabling enhanced encoding and extraction of secret image. GAN model performs two operations such as Generator (G) and Discriminator (D), where generator is performs embedding of secret image and discriminator ensures that embedded image is indistinguishable from the original image. To further enhance the GAN based feature extraction process, Morphological transformer is integrated into GAN generator and decoder. The major aim of the morphological transformer based generator is to enhance visual quality of stego image, assuring it highly resembles the cover image while managing and increasing the concealment effectiveness and robustness. Here, input vector z is fed as input to the generator and number of sampled gaussian distribution, then performs up-sampling convolution to attain $n \times n$ sized image that is $G(z)$.

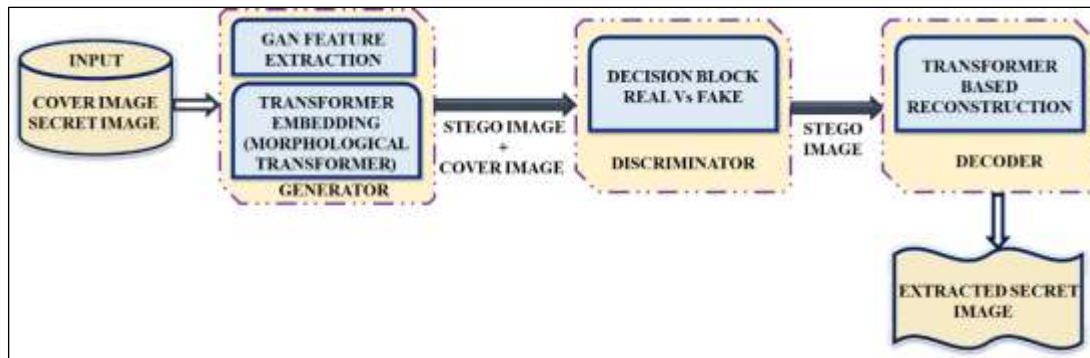


Figure 5: Morphological Transformer Based GAN.
Source: Authors, (2026).

Similarly, the discriminator based on morphological transformer improves the detection precision and accuracy by understanding the morphological and texture-based features. The original or converted image is fed into the discriminator as input which performs down-convolution to obtain realness value, which determines whether given image is real or fake. The main aim of generator is to produce images that dupes discriminator into considering they are real. Similarly, the goal of discriminator is to increase the probability of the image produced from real distribution $P_{data}(x)$, the expected value is given as $\mathbb{E}$,

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}(x)} [\log D(x)] + \mathbb{E}_{z \sim P_z(z)} [\log(1 - D(G(z)))] \quad (14)$$

Therefore, by incorporating morphological transformer with GAN model, enables enhanced performance with increased security and imperceptibility leading to highly effective image steganography process.

III. RESULT AND DISCUSSION

The proposed system is validated utilizing the Python software application to determine and analyse the performance effectiveness of the proposed model developed using DWT, NTRU based cryptosystem and Morphological Transformer based GAN. Additionally, their obtained results along with comparative analysis are also discussed and elaborated in this section.



Figure 6: Cover and Secret Image.

Source: Authors, (2026).

Fig. 6 represents the secret and cover image utilized in the proposed model, where six different images are taken as cover image for which six distinct images are taken as the secret image, where, each secret image is embedded using cover image using DWT. The utilization of DWT converts image pixels into frequency domains, enabling improved performance in terms of hiding the secret image.

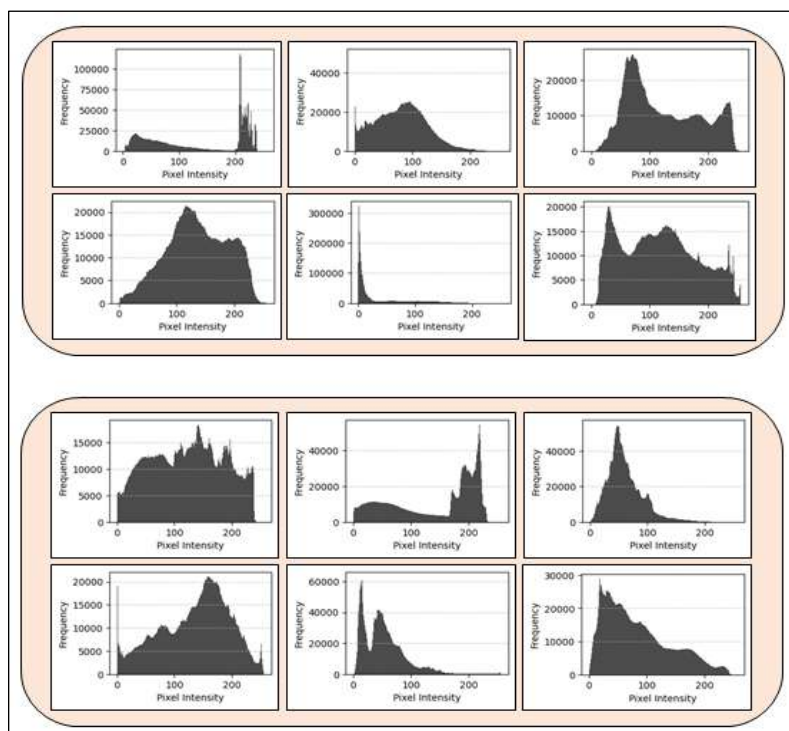


Figure 7: Histograms for cover and secret image.

Source: Authors, (2026).

Fig. 7 indicates the histograms attained for two sets of images that is cover and secret image where x-axis implies the pixel intensity and y-axis represents the frequency. The top plot shows histograms of secret image while bottom depicts histograms of cover image. Varying histograms showcases the difference in shapes, peaks and range of pixel intensities of the images.



Figure 8: Encryption of Secret Image.
Source: Authors, (2026).

Fig. 8 refers to secret image, encrypted image and their corresponding histograms, the first column of contains the 6 different secret image, the second column comprises of encrypted version of the secret image and the last column showcases the histogram showing the pixel intensity of the encrypted images. The histogram depicts uniform patterns referring to improved encryption process while maintain the image and information quality.



Figure 9: Encryption of secret image and decryption of stego image.
Source: Authors, (2026).

Fig. 9 displays the six different cover image, secret image, encrypted secret image, stego image, decrypted stego image and finally extracted image, this showcases the entire process of the proposed image steganography model. The encrypted secret is embedded with the cover image, that is the secret image is hidden behind the cover image forming the stego image, which further undergoes decryption and finally the extracted image displays the original secret image. Table 1 and 2 represents the performance metrics of the given images.

Table 1: Performance Metrics of First Three sets of Images.

Set 1		Set 2		Set 3	
Metrics (Secret vs. Encrypted)		Metrics (Secret vs. Encrypted)		Metrics (Secret vs. Encrypted)	
PSNR	6.80dB	PSNR	7.84dB	PSNR	8.37dB
MSE	13573.01	MSE	10681.06	MSE	9461.50
SSIM	0.0175	SSIM	0.0175	SSIM	0.0198
NCC	0.0000	NCC	0.0000	NCC	0.0004
(Cover vs. Stego)		(Cover vs. Stego)		(Cover vs. Stego)	
PSNR	44.16dB	PSNR	44.27 dB	PSNR	44.11dB
MSE	2.50	MSE	2.43	MSE	2.52
SSIM	0.9890	SSIM	0.9888	SSIM	0.9854
NCC	0.9997	NCC	0.9998	NCC	0.9995
(Encrypted vs. Decoded)		(Encrypted vs. Decoded)		(Encrypted vs. Decoded)	
PSNR	16.88dB	PSNR	16.88 dB	PSNR	16.88dB
MSE	1333.12	MSE	1333.64	MSE	1333.91
SSIM	0.9291	SSIM	0.9290	SSIM	0.9290
NCC	0.9683	NCC	0.9683	NCC	0.9682
(Secret vs. Extracted)		(Secret vs. Extracted)		(Secret vs. Extracted)	
PSNR	19.85dB	PSNR	19.71dB	PSNR	19.94dB
MSE	672.40	MSE	694.79	MSE	658.66
SSIM	0.3769	SSIM	0.4870	SSIM	0.4180
NCC	0.9578	NCC	0.8674	NCC	0.9238

Source: Authors, (2026).

Table 2: Performance Metrics of second Three sets of Images.

Set 4		Set 5		Set 6	
Metrics (Secret vs. Encrypted)		Metrics (Secret vs. Encrypted)		Metrics (Secret vs. Encrypted)	
PSNR	8.53dB	PSNR	5.88dB	PSNR	8.07dB
MSE	9125.68	MSE	16780.97	MSE	10129.50
SSIM	0.0203	SSIM	0.0078	SSIM	0.0186
NCC	0.0000	NCC	0.0002	NCC	0.0004
(Cover vs. Stego)		(Cover vs. Stego)		(Cover vs. Stego)	
PSNR	44.15dB	PSNR	44.16dB	PSNR	44.15dB
MSE	2.50	MSE	2.50	MSE	2.50
SSIM	0.9847	SSIM	0.9857	SSIM	0.9940
NCC	0.9998	NCC	0.9993	NCC	0.9996
(Encrypted vs. Decoded)		(Encrypted vs. Decoded)		(Encrypted vs. Decoded)	
PSNR	16.88dB	PSNR	16.88dB	PSNR	16.88dB
MSE	1333.40	MSE	1332.94	MSE	1334.25
SSIM	0.9291	SSIM	0.9291	SSIM	0.9290
NCC	0.9683	NCC	0.9683	NCC	0.9682
(Secret vs. Extracted)		(Secret vs. Extracted)		(Secret vs. Extracted)	
PSNR	19.82dB	PSNR	18.40dB	PSNR	20.04dB
MSE	677.80	MSE	939.08	MSE	643.83
SSIM	0.4606	SSIM	0.2565	SSIM	0.4505
NCC	0.9206	NCC	0.8524	NCC	0.9324

Source: Authors, (2026).

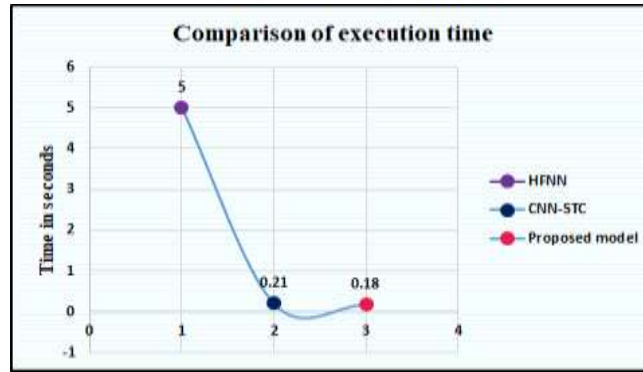


Figure 10: Comparison of execution time.
Source: Authors, (2026).

Fig. 10 showcases the comparison of execution time depicted by the proposed model against conventional approaches such as HFNN [1] and CNN-STC [2]. From the above chart it is notable that proposed model attained reduced execution time of 0.10 seconds, indicating the increased performance efficacy of the developed image steganography approach. While, the other two approaches attained slightly higher than the developed model.

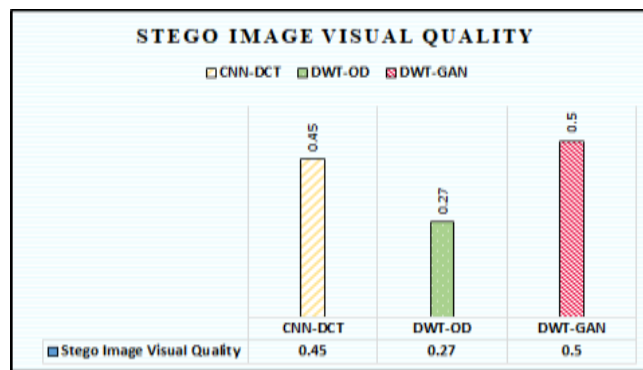


Figure 11: Comparison of stego image visual quality.
Source: Authors, (2026).

Fig. 11 depicts the comparison of stego image visual quality to determine the reliability of the proposed model which utilizes DWT based embedding strategy. The graph shows that, DWT based GAN obtained higher stego image quality when compared to other conventional techniques like CNN-DCT [19] and DWT-OD [20] which attained 0.45 and 0.27 stego image quality. Thus, it is visible that, proposed model showcases higher stego image visual quality when compared to other approaches.

Table 3: Comparison of Detection Accuracy.

Proposed Method		[3]Deg-Net (conventional method)	
Image set	Detection Accuracy	Image set	Detection Accuracy
Image set 1	55.79%	Set 1	78.88%
Image set 2	56.88%	Set 2	79.39%
Image set 3	54.32%	Set 3	62.76%
Image set 4	52.15%	Set 4	58.77%
Image set 5	49.07%	Set 5	55.06%

Source: Authors, (2026).

Table 3 represents the comparison of detection of accuracy between proposed method and Deg-Net [3] based image steganography model. This table comprises of the detection value accuracy for two models utilizing 5 different image sets, and from table it is evident that, proposed method depicts slightly reduced detection accuracy, indicating that the secret image is well hidden within the image, making it harder to predict. Thereby, improving the security and reliability of secure information transmission.

IV. CONCLUSION

The proposed model developed utilizing DWT, NTRU and morphological transformer based GAN achieves higher-capacity image steganography process with enhanced security and reliability. The implementation of DWT shows significantly improved performance in terms of attaining increased imperceptibility and robustness along with optimized frequency domain embedding. Furthermore, the incorporation of NTRU based encryption, ensures enhanced security by protecting the secret image against unauthorized access. Significantly, the utilization of morphological transformer based GAN offers precise and accurate encoding and extraction of secret image, thereby, further improving the information security and strengthening the proposed model effectiveness. Moreover, the developed model is validated using Python software that demonstrate, proposed model achieved increased steganographic performance by depicting highly efficient and secure digital communication, making it applicable for present digital communication age.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Jinsha Lawrence, Dinesh Kumar Budagam, Kanmani P, C. Jehan, Arul V H and S. Karthick.
Methodology: Jinsha Lawrence and Dinesh Kumar Budagam.
Investigation: Jinsha Lawrence and Dinesh Kumar Budagam.
Discussion of results: Jinsha Lawrence, Dinesh Kumar Budagam, Kanmani P, C. Jehan, Arul V H and S. Karthick.
Writing – Original Draft: Jinsha Lawrence.
Writing – Review and Editing: Jinsha Lawrence and Dinesh Kumar Budagam.
Resources: Dinesh Kumar Budagam.
Supervision: Dinesh Kumar Budagam, Kanmani P, C. Jehan, Arul V H and S. Karthick.
Approval of the final text: Jinsha Lawrence, Dinesh Kumar Budagam, Kanmani P, C. Jehan, Arul V H and S. Karthick.

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