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# SSII: Secured and high-quality Steganography using Intelligent hybrid optimization algorithms for IoT

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## ABSTRACT

Internet of Things (IoT) is a domain where the transfer of big data is taking place in every single second. The security of these data is a challenging task; however, security challenges can be mitigated with cryptography and steganography techniques. These techniques are crucial when dealing with user authentication and data privacy. In the proposed work, a highly secured technique is proposed using IoT protocol and steganography. This work proposes an image steganography procedure by utilizing the combination of various algorithms that build the security of the secret data by utilizing Binary bit-plane decomposition (BBPD) based image encryption technique. Thereafter a Salp Swarm Optimization Algorithm (SSOA) based adaptive embedding process is proposed to increase the payload capacity by setting different parameters in the steganographic embedding function for edge and smooth blocks. Here the SSOA algorithm is used to localize the edge and smooth blocks efficiently. Then, the hybrid Fuzzy Neural Network with a backpropagation learning algorithm is used to enhance the quality of the stego images. Then these stego images are transferred to the destination in the highly secured protocol of IoT. The proposed steganography technique shows better results in terms of security, image quality and the payload capacity in comparison with the existing state of art methods.

**INDEX TERMS**: Steganography, encryption, embedding process, Salp Swarm optimization, Hybrid Fuzzy Neural Network.

## 1. INTRODUCTION

In today's era security of confidential data is most important and developments in the field of computer security have presented steganography as a better method of obtaining secured data [1][2]. Steganography is the process of hiding secret data that can be in the form of a message, audio, image, or video into another image, audio, message, or video using embedding processes [3][4][5]. It is employed to protect secret data from malicious attacks[6][7]. The amount of data exchanged via the internet is increasing nowadays. Hence, Data security is termed as a serious issue while communication of data is processed over the internet. Dual techniques namely steganography and cryptography are used to provide secure information [8][9]. To provide more security to the data, cryptography is used together with the steganography technique [10][11]. Both methods play a significant role in information security [12].

With the help of cryptography, secret data can be easily encrypted[13]. Some of the main goals of cryptography are integrity, authentication, and confidentiality [14]. Then, the steganography process hides the encrypted data so that nobody can suspect that there exists secret data[15]. Normally, the steganography system includes three components such as cover-object, secret data, and stego-object. If the information is embedded in an image file (cover image) then the outcome is a stego-image object. Likewise, for the case of video, audio, and text for embedding with the following outcomes as stego-video, stego-audio, and stego-text respectively[16]. There are different types of covers in which secret information can be embedded. The Steganography approach seems to be a good one if it considers three parameters for the processing which means capacity, security, and image quality.

Generally, the steganography methods conceal an equal number of secret bits into each pixel of the cover image. Hence, they cause an equal degree of embedding distortion in the cover image. But, the individual pixels of any digital image exhibits complex statistical dependencies between them. Thus, the quality of the image is automatically reduced while

performing an equal number of bits changes in all pixels of the cover image. To tackle these issues different adaptive embedding processes have been introduced in the steganography process[17]. This adaptive embedding process embeds a variable number of bits in each pixel of the cover image[18]. Thus, most of the researchers focused on these adaptive techniques to improve the security of steganography methods[19]. Furthermore, the quality of edge pixels is not much affected after making changes during the embedding process. Thus, more secret bits can be embedded into edge pixels than smooth pixels[20]. The metaheuristic algorithms are used in most applications to solve optimization issues [21].

YN Rao [22] proposed a work to protect IoT communicated data in the cloud which is connected through the internet. A complex encryption and decryption technique is proposed to provide high data security. Only encryption and decryption is implemented, but data hiding is presenting in this paper and has more advantage that the existing works.
Shehab *et al.* [23], surveyed a comprehensive study on security issues in IoT networks. Various security requirements such as authentication, integrity, confidentiality were discussed. A comparative study of different types of attacks, their behavior, and their threat level that categorized into low-level, medium-level, high-level, and extremely high-level attacks and suggested possible solutions encounter these attacks were provided.

Now a day's protection of data with high payload capacity is the most important task while communicating secret data. In our proposed technique combination of Salp Swarm Optimization Algorithm and adaptive embedding, provides higher security as well as high payload capacity. Moreover, based on the proposed technique, various real-world tasks can be achieved easily. In the medical field, this technique will be very helpful like in an X-Ray copy, the details of the patient and their health problem can be stored without disturbing the X-ray film quality. This detail can only be detected with a key available to the diagnosing doctor. Similarly, the details of an original artist can be hidden within a painting/artwork.

### *1.1 Motivation and Contribution*

This work is principally motivated toward the improvement of new techniques to survive these impediments and to give better protection from existing steganalysis techniques. The particular issues in such a manner are momentarily examined underneath: One of the significant disadvantages of embedding in different bit planes is that a huge amount of noise is added because of this interaction. The interloper may attempt a counter assault by making a few changes to counter existing strategies. This is the motivation that there is a need to generate a technique for producing robust techniques with high-quality stego images and a high payload capacity of steganography.

The main contribution of this work is summarized as follows:

1. In this paper, a secured image steganography method is proposed based on an adaptive embedding process.
2. To increase the security of the hidden (secret) image, the hidden image is initially encrypted using a bit-level image encryption algorithm. This encryption method requires a single round of bit-level permutations but in two phases (diffusion and confusion stage) for giving excellent performance.
3. Also, a Salp Swarm Optimization Algorithm-based adaptive embedding process is proposed to embed the encrypted data into the cover image. This process embeds the secret data efficiently by setting optimal parameter values to smooth and edge blocks. Thus, the proposed method automatically increases the payload capacity with less distortion rate.
4. A hybrid Fuzzy Neural Network with a backpropagation learning algorithm is used to enhance the quality of the stego images. Then these stego images are transferred to the destination in the highly secured protocol of IoT.
5. The experiment is tried with different secret pictures and cover pictures and ensured that the created stego-picture has no noise or information loss.

The rest of the paper is structured as follows: Section 2 provides some related works on image steganography. Section 3 gives the detail about the proposed steganography method. Section 5 presents the simulation results and a comparison with existing works. Finally, the paper is concluded in Section 6.

## 2. RELATED WORKS

Some of the recent related works on image steganography are listed as follows:

Sun et al. [24] proposed Cloud Eyes, a cloud-based antimalware system. The proposed system provided efficient and trusted security services to the devices in the IoT network. Ukil et al. [25] studied the requirements of embedded security, provided methods and solutions for resisting cyber-attacks, and provided technology for tamper-proofing the embedded devices based on the concept of trusted computing.
Bairagi et al. [26] proposed three-color image steganography approaches for protecting information in an IoT infrastructure. The first and third approaches use three (red, green, and blue) channels, while the second approach uses two (green and blue) channels for carrying information. Dynamic positioning techniques have been used for hiding information in the deeper layer of the image channels with the help of a shared secret key.
Anwar et al. [27], developed a technique to secure any type of image especially medical images. They aimed to maintain the integrity of electronic medical information, ensuring the availability of that information, and authentication of that information to ensure that authorized people only can access the information. First, the AES encryption technique was applied in the first part. The ear print was also embedded in this work, where seven values were extracted as feature vectors from the ear image. The proposed technique improved the security of medical images by sending them via the internet and secured these images from being accessed by any unauthorized person.
Abdel Aziz et al. [28], surveyed the analysis of the security vulnerabilities and the risk factors detected in mobile medical apps. According to risk factor standards, these apps can be

categorized into remote monitoring, diagnostic support, treatment support, medical information, education and awareness, and communication and training for healthcare workers. Eight security vulnerabilities and ten risk factors detected by the World Health Organization (OWASP) mobile security project in 2014 have been analyzed.

Razzaq et al. [29], proposed a fused security approach based on encryption, steganography, and watermarking techniques. It decomposed into three stages; (1) encrypting the cover image using XOR operation, (2) embedding process done using least significant bits (LSBs) for generating the stego-image, then (3) watermarking the stego-image in both spatial and frequency domains. Experimental results proved that the proposed method was very much efficient and secured.

Jain *et al.*[30] , proposed a new technique for transferring the patient's medical information into the medical cover image by hiding the data using the decision tree concept. The coding is done in the form of different blocks that are evenly distributed. In concealment, secret code blocks are assigned to the cover image to insert the data by the mapping mechanism based on breadth-first search. RSA algorithm was used to encipher the data before embeddings.

Yehia *et al.* [31], surveyed various healthcare applications based on wireless medical sensor networks (WMSN)[32] that can be implemented in an IoT environment. Also, discussed the security techniques are used for handling the security issues of healthcare systems especially hybrid security techniques.

Zaw and Phyo [33], presented an algorithm based on dividing the original image into a group of blocks, where these blocks are arranged in the form of turns using a transformation algorithm. After that, the transformed image is encrypted using the Blowfish algorithm. It was found that the correlation decreases and the entropy increase by increasing the number of blocks through using smaller block sizes.

Anupriya and Sarita[34] discussed the performance evaluation of secret image steganography approaches for data and image security. Pranab *et al* [35]developed Modified LSB (MLSB) substitution and data mapping methods for image steganography. At first, the secret image was pre-processed using the data mapping approach and embedded into the host image using MLSB.

In general, most of the LSB methods were not depending on pixel correlation and the contents of the images. Thus, it could be identified through RS analysis. Hence, there is a requirement for certain protective measures for increasing the security of LSB-based steganography methods. To tackle this issue, an edge detection process has been included in the LSB-based steganography method. Also, the secret images should be encrypted before embedding them into the cover image for increasing the security level. The security level of certain existing methods has been reduced because of the lack of encryption algorithms before the embedding process. Odelu et al. [36] proposed another RSA-based CP-ABE conspire with consistent size secret keys and ciphertexts. Then demonstrated to be secure against a picked ciphertext foe, just as being an effective arrangement with the expressive AND door access structures. The proposed plot in this paper is appropriate for arrangement on battery-restricted cell phones.

Yaseen *et al.*[37] used Vernam cipher algorithm to encrypt the secret image. Here, the keystream was generated with the help of Geffe Generator. But, this Geffe Generator is not a secure one. Then, hybrid Kirchand Sobel edge detectors were used to localize the edges of the cover image. Then, the LSB method was used to hide the secret image into the cover image. Hemalatha et al. [38] utilize the behavior of animals i.e particle swarm optimization algorithm for better embedding rate and better visual quality. Maheshwari et al. [39] utilize the two optimization techniques Genetic Algorithm (GA) and Particle Swarm Optimization used for improving the performance of the hiding process of steganography system. Mohsin et al. [40] give novel image steganography based on particle swarm optimization (PSO) algorithm in which secret data concealed based on pixel selection in the spatial domain, for high embedment capacity. Fazli et al. [41] gives the technique of Particle Swarm Optimization (PSO) [63] algorithm to search best ways and to search best substitution matrix for transforming the secret message in each block, instead of finding only one optimal substitution matrix for the whole cover-image.

The character based bunch check conspire was recently proposed to make VANET safer and productive for practical use. Tzeng et al. [42] bring up that the current IBV conspire exists some security hazards. This paper gives an improved plan that can fulfill the security and protection wanted by vehicles. The proposed plot gives the provable security in the arbitrary prophet model.

Mohsin et al. [43] give the novel strategy of Image Steganography in Spatial Domain based on Particle Swarm Optimisation Algorithm for High Embedding Capacity.

Khan et al. [44] unique mark biometric–based self-validation and deniable confirmation plans, which empower a recipient to recognize wellspring of the message however not to demonstrate the personality of the sender to a outsider.

EL-Latif et al. [45] present another system for secure data in fog cloud IoT. In the system, the client in one area installs his/her significant information through the proposed quantum steganography convention and transfers the covered information to the haze cloud. The proposed recipient in another area gets the information from the mist cloud and concentrates the planned substance through the proposed extraction approach.

Khan et al. [46] gives the technique to conquer the inborn security shortcomings of the 2-factor authentication technique, we propose enhancements and security fixes that endeavor to fix the susceptibilities of his plan. The proposed security upgrades can be joined in the 2-factor authentication technique for accomplishing a safer and vigorous two-consider client verification WSNs.

Elhoseny et al. [47] gives a hybrid security model for getting the indicative content information in medical images. The proposed mixture encryption blueprint is fabricated utilizing a combination of Progressed Encryption Standard, and Rivest, Shamir, and Adleman calculations.

Waqar et al. [48] proposes a technique for cloud users' data privacy dependent on information base construction update and dynamic reproduction of meta information for the conservation of security.

Khari et al. [12] proposed the elliptic Galois cryptography protocol. In this protocol, a cryptography technique is used to encrypt confidential data that came from different medical sources.

Horng et al. [49] give a safe plan that can accomplish the security and protection prerequisites, and conquer the shortcomings of SPECS. Additionally, this paper show the effectiveness benefits of plan through execution assessments as far as confirmation postponement and transmission overhead.

Meng et al. [50] proposed novel steganography dependent on picture to-picture interpretation by adding steganography module and steganalysis module to CycleGAN, adjusting to the secret correspondence and protection safeguarding of the IoT [61][62]. Steganalysis network is utilized to improve the counter recognition capacity of stego picture

One of the most mainstream versatile hiding processes is pixel difference histogram (PVD) steganography. This strategy implanted more confidential information into edge portions and less information into smooth portions. Pradhan et al. [51] joined LSB, PVD, and Exploiting modification direction (EMD) techniques to shape another half and half picture steganography algorithm. Here, the edge zone utilized consolidated LSB and PVD, while the smooth zone utilized the combined LSB and EMD approach. However, they have not utilized any encryption cycle for mystery pictures and there is no ideal calculation for edge and smooth pixel ID. The proposed algorithm attempts to take care of all the issues related to the current algorithms by building up effective mystery picture encryption calculations and a proficient Salp Swarm Optimization Algorithm-based versatile installing measure.

## 3. PROPOSED METHODOLOGY

In this work, IoT-based Secured and high-quality Steganography is proposed using hybrid algorithms for Big Data. Steganography technique is proposed for communicating secret data based on encryption. Normally, the digital image includes dissimilar picture elements named pixels. In this work, a grayscale image is used as a cover image. Therefore, an image is represented by an array that includes many bytes. The proposed system mainly includes four sections: Image encryption, Embedding phase, Quality enhancement, and Extraction phase. The block diagram of the proposed steganography scheme is shown in Figure 1. As shown in figure 1, Initially, the image of Lena is considered as cover, and the image of the Aeroplane is considered as a hidden image. Here, the size of the secret data should be less than the size of the cover image. Then, the hidden image is converted into a cipher image using Binary bit-plane decomposition (BBPD) based image encryption. This encryption algorithm is worked based on piecewise linear chaotic maps (PWLCM).

The next stage is the embedding phase, where the secret data gets embedded into the cover image. In this embedding process, the smooth and edge portion of the image is obtained by setting an objective function for *Salp Swarm Optimization Algorithm* based on the Manhattan Distance operator. The bigger the output of the objective functions the high the probability of edge presence. Hence, the automatic thresholding function is used to identify the edge pixels in the image. Then, the pixel values in the hidden image are embedded into the cover image based on the steganographic embedding function. This process will use different parameter values for edge and smooth areas. Finally, we will obtain the stego-image. But, the quality of this stego image is not good enough. Thus, a hybrid Fuzzy Neural Network (HFNN) with a backpropagation learning algorithm is used to enhance the quality of the stego images. This network contains two sections: a fuzzy processing unit and a conventional backpropagation network. A membership function is used in the fuzzy processing unit to process the inputs and the processed data will be given as input to the backpropagation network for further processing. Then, the output is compared with the expected output and the network connection weights are adjusted based on the mean squared error to obtain good quality images. Further, stego images with enhanced quality are transferred through IoT protocol with higher security as shown in the figure. As shown in Figure 1, the Internet of Things (IoT) makes it possible to connect a wide range of smart devices to the internet. The evolution of medicine can be aided by IoT by incorporating sensors such as environmental sensors inside the internal environment of a small room with the specific purpose of monitoring a person's health with a type of assistance that can be controlled remotely. In this paper, IoT is used to propose digital image steganography as a method to improve medical data security, confidentiality, and integrity. When embedding additional data within medical images, medical image steganography requires extreme caution because the additional data must not degrade the image quality. Many of the medical diagnosis exploration systems are based on medical study images. In the IoT scenario, combining encryption and steganography can ensure secure data transfer over the internet.

The next process is extraction which includes the same steps for data embedding but in reversible order.

### *3.1 IMAGE ENCRYPTION*

In the hidden image encryption process, a BBPD method is used to decompose the hidden image into eight binary bitplanes [52]. This BBPD method gives binary representation $(b_{m-1},....b_1,b_0)$ for the non-negative decimal number $D$ as given below:

$$D=\sum_{j=0}^{m-1} b_j \cdot 2^j = b_0 \cdot 2^0 + b_1 \cdot 2^1 + .... + b_{m-1} \cdot 2^{m-1} \quad (1)$$

The pixel values of the grayscale images are in the range of [0,255]. Hence, they are decomposed into eight binary bitplanes.

The encryption module contains two Stages: The diffusion stage and the Confusion stage. Here, two binary keystreams are generated with the help of a secret key, $K_1(y_0,\delta_1)$ before entering into the diffusion and confusion stage. The key streams are generated using a piecewise linear chaotic map (PWLCM). The PWLCM [30] is defined as follows:

$$y_{j+1}=F(y_j,\delta)=\begin{cases} y_j/\delta & y_j \in [0,\delta) \\ (y_j-\delta)/(0.5-\delta) & y_j \in [\delta,0.5) \\ F(1-y_j,\delta) & y_j \in (0.5,1) \end{cases} \quad (2)$$

Where $\delta \in (0,0.5)$ represents the control parameter and $y_j \in (0,1)$ represents the initial condition for PWLCM. The initial value of $y_0$ and $\delta_1$ should be set for encrypting the hidden image of size $M \times N$. Then, the PWLCM map is iterated $M \times N$ times to obtain the chaotic sequence or keystream $Y = \{y_1, y_2, ... y_{MN}\}$. Then, this $Y(j)$ is converted into an integer sequence $Y_1(j)$ using the following expression:

$$Y_1 = \mathrm{mod}(floor(Y \times 10^{14}), 256) \quad (3)$$

Then, BBPD is used to decompose the keystream $Y$ into 8 bitplanes. Then, these bitplanes are grouped into two groups to obtain binary sequences $k_1$ and $k_2$. These groups are formed by arranging the bits from left to right and higher bitplane to lower bitplane.

*Diffusion stage:* The following steps are performed in the diffusion stage.

1. Add all the elements $P_2$ as given below:

$$S_1 = \sum_{j=1}^{4MN} P_2(j) \quad (4)$$

2. Perform cyclic shift operation in $P_1$ the matrix to obtain $P_{11}$. Here, the elements in $P_1$ the matrix are right-shifted by $S_1$ bits.
3. Encrypt the 1st element of $P_{11}$ with the previous element of $P_{11}$ and the 1st element of $P_2$ with the first element of $k_1$ as given below:

$$Q_1(j) = P_{11}(j) \oplus P_{11}(j-1) \oplus P_2(j) \oplus k_1(j) \quad (5)$$

4. Add all the elements $Q_1$ as given below:

$$S_2 = \sum_{j=1}^{4MN} Q_1(j) \quad (6)$$

5. Perform cyclic shift operation in $P_2$ the matrix to obtain $P_{22}$. Here, the elements in $P_2$ the matrix are right-shifted by $S_2$ bits.
6. Encrypt the 1st element of $P_{22}$ with the previous element of $P_{22}$ and the 1st element of $Q_1$ with the first element of $k_2$ as given below:

$$Q_2(j) = p_{22}(j) \oplus p_{22}(j-1) \oplus Q_1(j) \oplus k_2(j) \quad (7)$$

*Confusion stage:* The following steps are performed in the confusion stage:

1. Add all the elements in $Q_1$ and $Q_2$ as given below:

$$S_3 = \sum_{j=1}^{4MN} Q_1(j) + Q_2(j) \quad (8)$$

2. Generate keystream $Z_1$ and $Z_2$ using the secret key $K_2(z_0, \delta_2)$. The following expression is used to generate the initial value $a_0$

$$a_0 = \mathrm{mod}(z_0 + S_3/4MN, 1) \quad (9)$$

Generate a new chaotic sequence $A = \{a_1, a_2, ... a_{2MN}\}$ by iterating PWLCM $2 \times 4MN$ times. Subsequently, $A$ is divided into two equal sequences:

$$A_1 = \{a_1, a_2, ... a_{4MN}\} \quad (10)$$

$$A_2 = \{a_{MN+1}, a_{MN+2}, ... a_{4MN}\} \quad (11)$$

Then, these sequences $A_1$ and $A_2$ are converted into integer sequence $Z_1$ and $Z_1$ using the following expression:

$$Z_1 = \mathrm{mod}(floor(A_1 \times 10^{14}), 4MN) + 1 \quad (12)$$

$$Z_2 = \mathrm{mod}(floor(A_2 \times 10^{14}), 4MN) + 1 \quad (13)$$

3. Obtain the encrypted row vector $R_1$ by swapping the elements in $Q_1$ and $Q_2$ as given below:

$$temp = Q_1(j) \quad (14)$$

$$Q_1(j) = Q_2(Z_1(j)) \quad (15)$$

$$Q_2(Z_1(j)) = temp \quad (16)$$

4. Obtain the encrypted row vector $R_2$ by swapping the elements in $Q_1$ and $Q_2$ as given below:

$$temp = Q_2(j) \quad (17)$$

$$Q_2(j) = Q_1(Z_2(j)) \quad (18)$$

$$Q_1(Z_2(j)) = temp \quad (19)$$

5. Transform the row vectors $R_1$ and $R_2$ into $M \times N$ the image to obtain the cipher image.

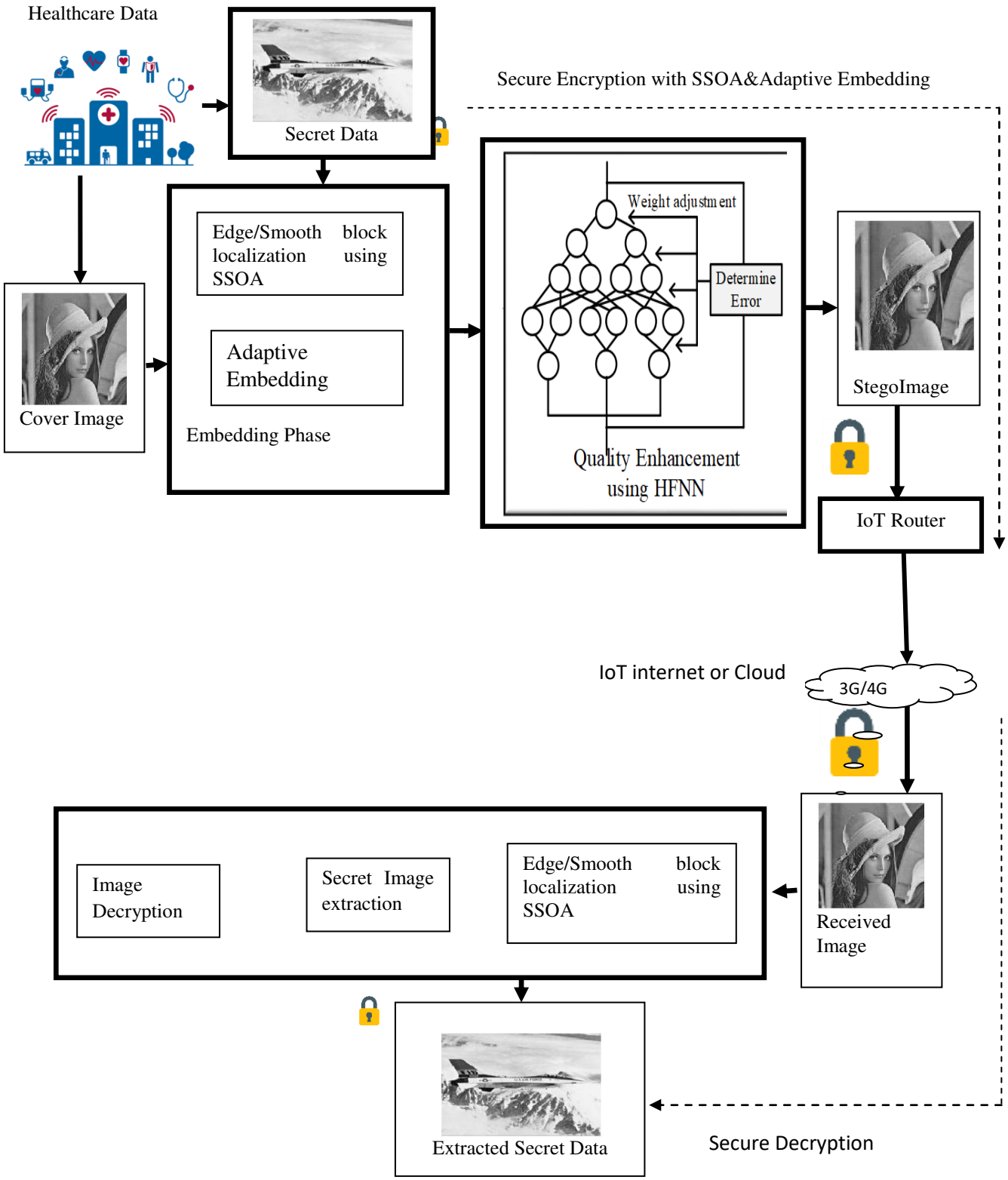


**FIGURE 1** Block diagram of the proposed steganography scheme

### *3.2 SALP SWARM OPTIMIZATION ALGORITHM (SSOA) BASED ADAPTIVE EMBEDDING*

The pixel values of the cover images are in the range of [0,255]. In this work, the secret image data is embedded in both smooth region and edge region by setting different parameter values in the steganography embedding function. In the proposed embedding process, the smooth and edge pixels of the image are obtained by setting an objective function for *Salp*

*Swarm Optimization Algorithm (SSOA)* [53] based on the Manhattan Distance operator ($l_1-$norm) [54]. The maximum value of the objective function represents the existence of edges. Then, the secret bit values are embedded into the cover image based on the steganography embedding function [55]. This process will use different parameter values for edge and smooth areas. Finally, we will obtain the stego-image.

***3.2.1 EDGE/SMOOTH BLOCK LOCALIZATION:*** In this work, an SSOA algorithm is proposed to localize the edge/smooth pixels in the cover image by identifying optimal threshold value based on the maximization of the objective function (Manhattan Distance operator ($l_1-$norm)). The SSOA is a population-based optimization algorithm that mimics the swarm behavior of salps in nature. The SSOA begins with the random initialization of individuals. The swarm of salps consists of two kinds of individuals: a leader and followers.

To localize the edge/smooth block, m salps are dispensed on an image $C$ with a size of $M \times N$ in a random manner. The 2-D representation for the swarm S of m salps is given in (20). Here, the food source (i.e., optimal threshold) is considered as the target of this swarm in the search space called T. After initializing the population as in (20), the fitness of each search agent should be determined to obtain the optimal threshold value for edge detection. Here, the $l_1-$norm is computed by each salp in the SSOA. When any salp discovers itself in the pixel positioned at $(i, j)$ of cover image $C$, the Manhattan Distance of all 8-neighboring pixels from the center pixel $r$ is calculated using (21).

$$S_i = \begin{bmatrix} s_1^1 & s_2^1 & \dots & s_n^1 \\ s_1^2 & s_2^2 & \dots & s_n^2 \\ \vdots & \vdots & \vdots & \vdots \\ s_1^m & s_2^m & \dots & s_n^m \end{bmatrix} \tag{20}$$

This objective function determines the discrete derivatives of the neighboring pixels to provide evidence for the existence of edge pixels. The maximum value of the objective function represents the higher chance of edges.

$$f = \left|C_{((i-1),(j-1))} - r\right| + \left|C_{(i-1,j)} - r\right| + \left|C_{(i-1,j+1)} - r\right| + \left|C_{(i,j-1)} - r\right| + \left|C_{(i,j+1)} - r\right| + \left|C_{(i+1,j-1)} - r\right| + \left|C_{(i+1,j)} - r\right| + \left|C_{i+1,j+1} - r\right| \tag{21}$$

Where $|\cdot|$ represents the operator for getting absolute values and $r$ represents the center pixel at a position $(i, j)$ within the cover image $C$, wherein the latest salp is positioned. After obtaining the fitness of all salps, the best search agent is considered the leader salp. In SSOA, the location of the leader particle is computed as:

$$s_j^1 = \begin{cases} T_j + \varepsilon_1\left(\left(B_U^j - B_L^j\right)\varepsilon_2 + B_L^j\right) & \varepsilon_3 \geq 0.5 \\ T_j - \varepsilon_1\left(\left(B_U^j - B_L^j\right)\varepsilon_2 + B_L^j\right) & \varepsilon_3 < 0.5 \end{cases} \tag{22}$$

Where $s_j^1$ represents the position of leader and $T_j$ represents the position vector of food source, $B_U^j$ and $B_L^j$ represents the upper and lower bounds respectively. $\varepsilon_2$ and $\varepsilon_3$ are random values in the range of 0 and 1. The important parameter $\varepsilon_1$ is determined using the following expression

$$\varepsilon_1 = 2e^{-\left(\frac{4n}{N_{\max}}\right)^2} \tag{23}$$

Here, $n$ and $N_{\max}$ represents the present and a maximum number of iteration. Afterward, SSOA updates the follower's positions using

$$s_j^i = 0.5 \times \left(s_j^i + s_j^{i-1}\right) \tag{24}$$

Where $s_j^i$ represents the position of i[th] follower in j[th] dimension. In SSOA, all the salps are initiated randomly. Then, the fittest salp is selected by evaluating the objective function of all salps. Equations (22) and (24) are used to update the position vectors of leaders and followers respectively. In the meantime, the parameter $\varepsilon_1$ is updated using (23). These processes are repeated until the maximum number of iterations to return the best threshold value T for edge detection. The algorithm for getting optimal threshold using the SSOA algorithm is provided in Algorithm 1.

**Algorithm 1** SSOA algorithm for edge/smooth pixel localization

1. Initialize a maximum number of iterations $N_{\max}$, population size m, parameters of SSOA, and define the objective function.
2. Initialize the positions of salps on cover image C in a random manner
3. Set $n := 1$
4. Repeat
5. Calculate the fitness function of each search agent positioned at the coordinate $(i, j)$ of the cover image $C$ using (21)
6. Select T as the best search agent
7. Adjust the main parameter of SSOA $\varepsilon_1$ using (23)
8. for $(i = 1 : i \leq m)$ do
9. if $i == 1$ then
10. Update leader's position using (22)
11. else
12. Update follower's positions using (24)
13. end for
14. Check whether any search agent does not belong to the upper and lower bounds and amend it.
15. Determine the fitness function of the search agent.
16. Update T if there is a better solution
17. Set $n = n + 1$
18. until $n < N_{\max}$
19. Return optimal T

After obtaining the edge/smooth pixels of the cover images using the optimal threshold value, the cover image is divided into non-overlapping k-pixel blocks and their corresponding gray values are $g=(g_1,g_2,...g_k)$. Based on the presence of edge pixels, the blocks are identified as edge block and smooth block as given in (25)

$$class=\begin{cases} edgeblock & if\ N_e > N_s \\ smoothblock & if\ N_e < N_s \end{cases} \quad (25)$$

Where, $N_e$ and $N_s$ represent several edge pixels and smooth pixels respectively.

***3.2.2 Embedding process:*** During the embedding process, the proposed method uses two different parameter values in the steganography embedding function. Specifically, the low parameter values $\rho_l$ and $b_s=1+\sum_{j=1}^{k}\binom{k}{j}\binom{\rho_l}{j}\times 2^j$ are used by the smooth blocks. Alternatively, high parameter values $\rho_h$ and $b_e=1+\sum_{j=1}^{k}\binom{k}{j}\binom{\rho_h}{j}\times 2^j$ are used by the edge blocks. The detailed steps for the embedding process of each k-pixel block are listed below:

1. Compute the steganography embedding function $F(g)=Ag^T \bmod b_1$, where $b_1=b_s$ and $\rho_1=\rho_l$ for smooth block, $b_1=b_e$ and $\rho_1=\rho_h$ edge block. Also, $A=(a_1,a_2,....a_k)$, $a_j=(2\rho_1+1)^{j-1}$
2. Compute $u=\mathrm{mod}(s,b_1)$ and $d=u-F(g)\bmod b_1$, where, $s$ represents the encrypted bit values in the secret image. The pixels in the k-pixel block are not modified when $d=0$. Then, the secret value $s$ is replaced with $(s-u)/b_1$ and the pixel values are modified by running the next k-pixel block. If $d>0$ the move to step 3.
3. Determine the vector $v$ by considering the condition $F(v)=d$ and $\|v\|_1 \le \rho$.
4. Compute $g'=(g'_1,g'_2,....g'_k)$ using $g'=g+v$ and $g'=(g'_1,g'_2,....g'_k)$ is adjusted to $g''=(g''_1,g''_2,....g''_k)$, if the stego-pixel value is affected by over/underflow problems as given below:

$$g''=\begin{cases} g'-b_1 & g'>255 \\ g'+b_1 & g'<0 \\ g' & 0\le g'\le 255 \end{cases} \quad (26)$$

5. Check the block $g''=(g''_1,g''_2,....g''_k)$ using the optimal threshold value obtained from the proposed edge localization algorithm to identify whether it belongs to smooth block or edge block. When the block type (edge/smooth) of $g''$ is as same $g$, no modification is needed. Because the secret digits have been embedded effectively. Then, the block $g$ and the secret value $s$ are replaced with block $g''$ and $(s-u)/b_1$ respectively. When the block type $g''$ is not the same as $g$ efficient extraction of the secret digit is not possible at the receiver side. Thus, one should move to adapt step 6.
6. This adapting step contains two events:
Event 1: Modify the pixels values for guaranteeing the same block type as the block before embedding. Determine $v^1=v_1^1,v_2^1,...v_k^1$ by considering the following conditions. (i) block $g$ and $g'=g+v^1$ should be in the same block type. (ii) $F(g+v^1)=u$. (iii) $0\le g+v^1\le 255$. (iv) the value $\|v^1\|_2$ is minimized.
Event 2: Adjust the embedding secret digit in the $k$-pixel block. If $b_1=b_s$ then $b_2=b_e$, Otherwise, $b_2=b_s$. Compute $u'=\mathrm{mod}(s,b_2)$. Then, the digit $u'$ is embedded into the block. Determine $v^2=v_1^2,v_2^2,...v_k^2$ by considering the following conditions: (i) block $g$ and $g'=g+v^2$ should be indifferent block types. (ii) $F(g+v^2)=u'$. (iii) $0\le g+v^2\le 255$. (iv) the value $\|v^2\|_2$ is minimized.
7. Here, event 1 will provide a higher payload with minimum embedding distortion when $\frac{\log_2 b_1}{\|v^1\|_2} > \frac{\log_2 b_2}{\|v^2\|_2}$. Then, the block $g$ and the secret value $s$ are replaced with block $g+v^1$ and $(s-u)/b_1$. For the other condition, event 2 will provide a higher payload with minimum embedding distortion. In this event, the block $g$ and the secret value $s$ are replaced with block $g+v^2$ and $(s-u')/b_2$ respectively. Repeat the above steps up $s=0$ for obtaining the stego image. The example for embedding using SSOA optimized adaptive embedding process is shown in Figure 2.

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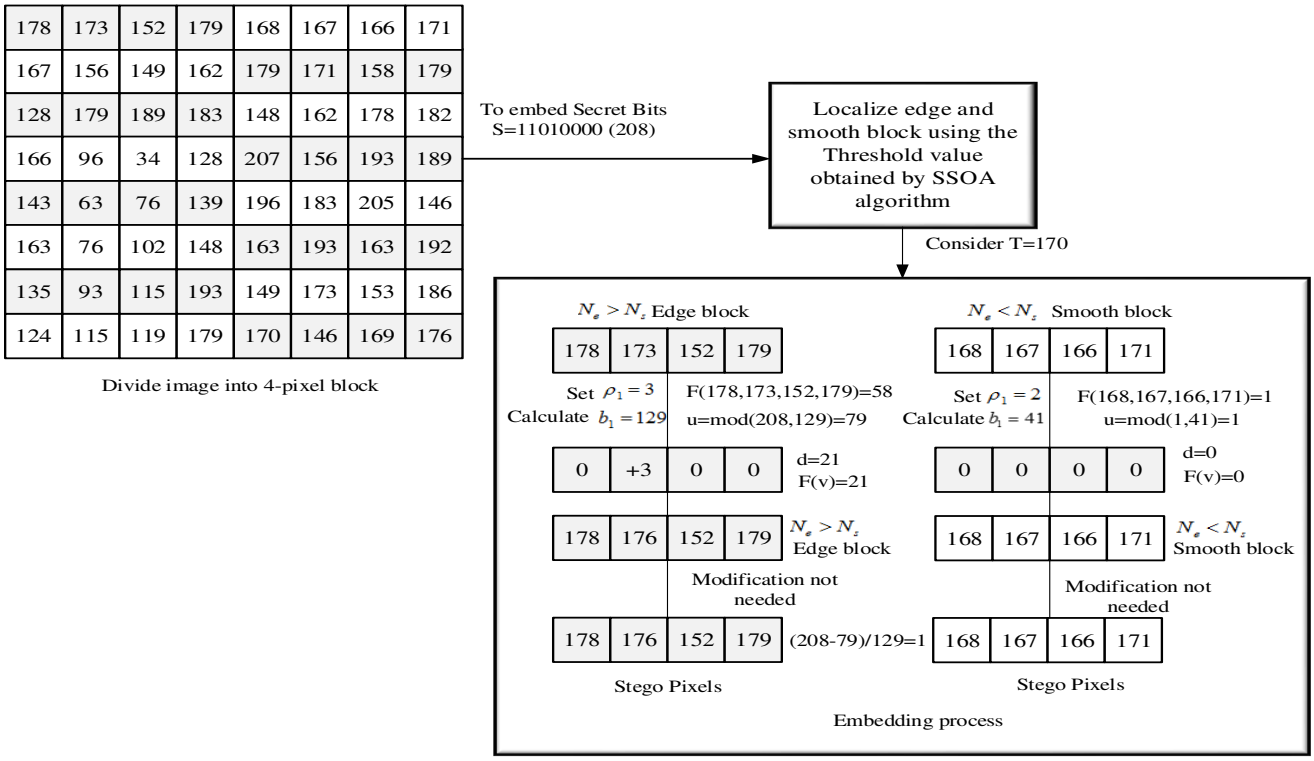


**FIGURE 2** Example for SSOA optimized adaptive embedding

In this example, the image is divided into the 4-pixel block. Then, the parameter value for the smooth and edge blocks are considered as $\rho_l = 2$ and $\rho_h = 3$. Here, the secret bits from the hidden image are considered as $s = 1101000$. Then the secret data is embedded using the steps (1-7) presented in the embedding process to get the stego image. But, the quality of this stego image is not good enough. Thus, the quality of this stego image is enhanced using HFNN with a backpropagation learning algorithm.

### *3.3 QUALITY ENHANCEMENT USING HFNN WITH BACKPROPAGATION LEARNING*

The quality of the obtained stego image is not good enough. Hence, there is a requirement for a post-processing method based on the specific intelligent system. This stage is required for the reduction of probabilities of statistical identification and other kinds of image manipulation attacks. In this work, an HFNN with a Backpropagation learning algorithm is used to enhance the quality of the image. Generally, neural networks resemble inhomogeneous HFNN. Neural networks are defined as a framework that can mimic the way the human brain learns[56]. The block diagram representation for stego image quality enhancement using HFNN is shown in Figure 3. Here, the stego image is converted into binary bit values for the identification of the free bits and the bits that embrace secret bits. A buffer is constructed for holding the free bits that are not utilized by the embedding process.

Furthermore, the statistical and visual features [64] are extracted from the stego and cover images. Here, the chi-square probability and the Euclidian norm are used to represent the statistical and visual features respectively. The free bits buffer and the two features of the stego image are given as input to the HFNN. Then, the cover features are compared with the outputs of HFNN. If the outputs are matched with the features of the cover image, a new stego image is formed by assembling the modified free bits with the secret bits. If not, the weights of HFNN are adjusted through a backpropagation learning algorithm.

There are five layers in HFNN, they are denoted as the input layer, fuzzification layer, rule layer, inference layer, and defuzzification layer as in [56]. The HFNN has been trained using five layers back-propagation, the input neurons obtain inputs from free bits buffer, statistical and visual features. After that, the inputs are broadcasted to all hidden neurons in the second layer (fuzzification layer). In this layer, fuzzy processing is performed on input features using the membership function. Here, the bell-shaped Gaussian membership function is used for the good approximation of input space. This bell-shaped function gives different forms of membership functions for the input features by varying the parameter values. In the rule layer, the firing strength of the fuzzy rules is computed using the logical 'AND' operator. The inference layer performs OR operations on fuzzy inference. The defuzzification layer will give the output of HFNN. In HFNN, the nodes of all layers are connected through the weight parameter.

### *3.4 EXTRACTION PHASE*

The hidden image extraction process includes the same steps as embedding but in reversible order. Here, the original cover image is not required to extract the secret image. Initially, the optimal threshold value is calculated by the SSOA algorithm for the reduction of smooth and edge blocks in the stego image. Subsequently, the enhanced stego image is divided into k-pixel blocks as same as the embedding process.

## 4. SIMULATION RESULTS AND DISCUSSION

In this section, the performance of the proposed steganography scheme is evaluated in terms of stego image quality, payload capacity, and security. Also, the performance analysis of the proposed scheme is validated by comparing it with other existing works like the Vernam Algorithm [37] and the hybrid method of LSB Substitution, PVD, and EMD [51]. The proposed steganography scheme is simulated in a Matlab R2019 environment with intel 8 GB RAM under the Windows 10 operating system. The 8-bit grey-level images such as Lena, Bell pepper, and Baboon are taken as the sample cover images each with a pixel size of 225 × 225. Also, 8-bit grey-level images such as Cameraman $(64\times64)$, Airplane images $(128\times128)$, and Barbara $(192\times192)$ are taken as sample hidden images with three different file sizes 5kB, 10kB, and 15kB respectively.

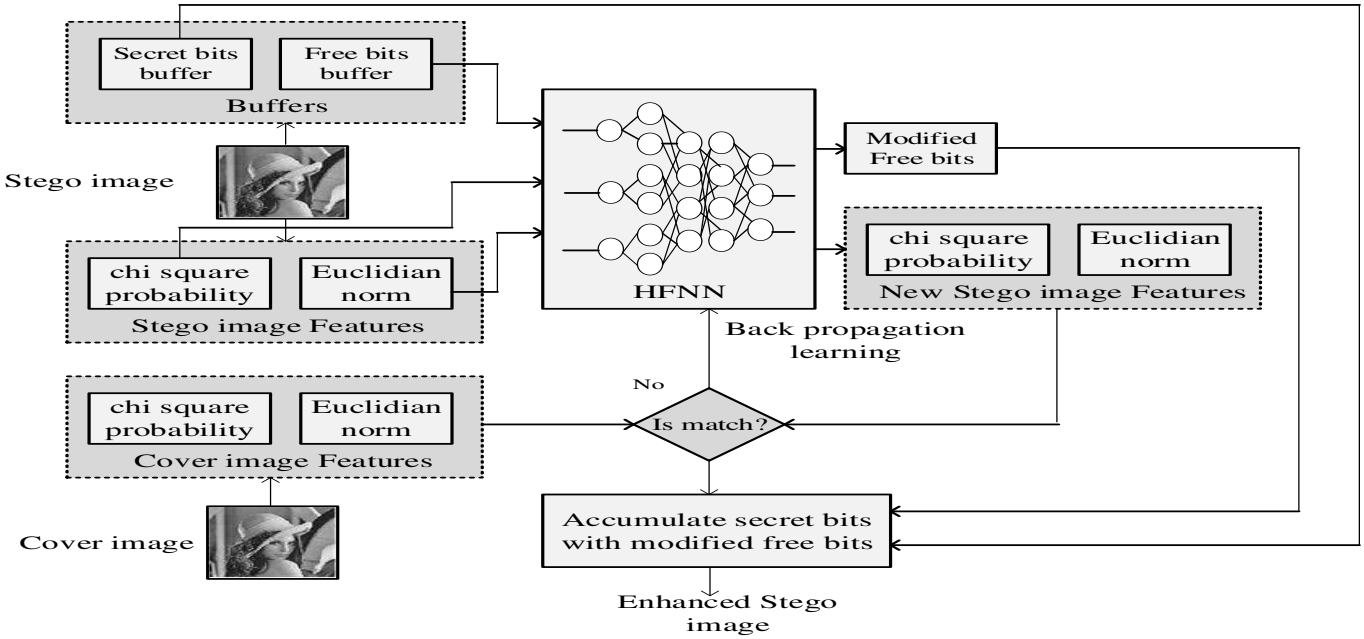


**FIGURE 3** Stego image quality enhancement using HFNN

These cover and hidden images are taken from the USC-SIPI image database [57] and they are illustrated in Figure 4. For the evaluations of this paper, we have implemented this technique on approximately 100 images, out of these, three different hidden images are embedded separately into three cover images. The corresponding stego images obtained by the proposed steganography scheme are shown in Figure 5(c). Here, the detailed steps for the proposed steganography scheme have been analyzed by taking an example of embedding of secret Barbara image into the Lena cover image. Initially, the secret Barbara image is encrypted using BBPD based image encryption algorithm. The encryption process of the secret Barbara image is shown in Figure 5. Here, the BBPD method is initially used to decompose the hidden image into eight binary planes as shown in Figure 5(b). Then, the binary bit planes are encrypted by performing a diffusion and confusion process using the keystream generated through PWLCM. The Encrypted image for Barbara's hidden image is shown in Figure 5(c).

In the proposed embedding stage, the edge pixels of the cover image are identified by the SSOA algorithm. Then, the encrypted hidden image is embedded into the cover image by setting different parameter values for edge and smooth blocks. Figure 6 illustrates the embedding process output of the proposed steganography method.

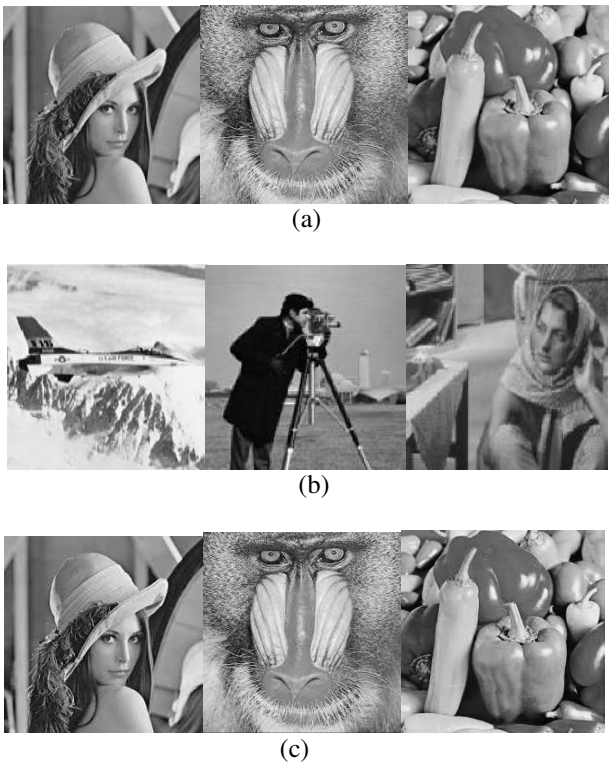


**FIGURE 4** Sample image sets (a) Cover images (b) Hidden images (c) Stego images

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During the extraction stage, the embedding process is performed in reverse order to extract the encrypted hidden image from the received stego image. It does not require the cover image. Then, the extracted hidden image is decrypted as shown in Figure 7. From this figure, one can understand that the proposed method can efficiently extract the hidden image without affecting the quality of the image.

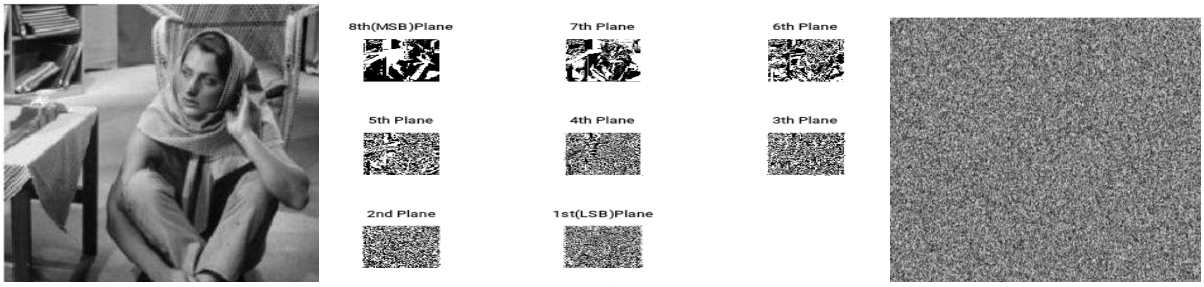
### *4.1 IMAGE QUALITY ANALYSIS*

The image quality metrics are used to determine the quality of the stego image. The image quality analysis of the proposed work based on different performance metrics is explained in this section.

Here, the learning algorithm used is the backpropagation method. This learning method reduces the sum of square error between the desired output and actual output value over each iteration.

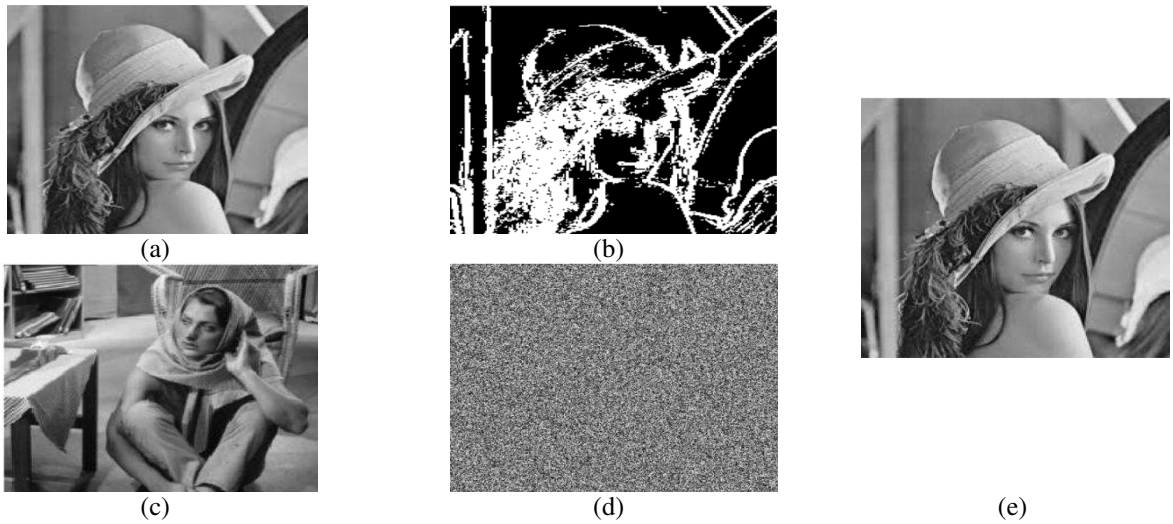
$$E = \frac{1}{2}\sum\left(D_i - O_i\right)^2 \quad (27)$$

Where, $D_i$ and $O_i$ represent desired and actual output ith node in the output layer respectively. Here, the weight values of all the layers in HFNN are adjusted by the training pattern of the backpropagation algorithm up to matching is achieved



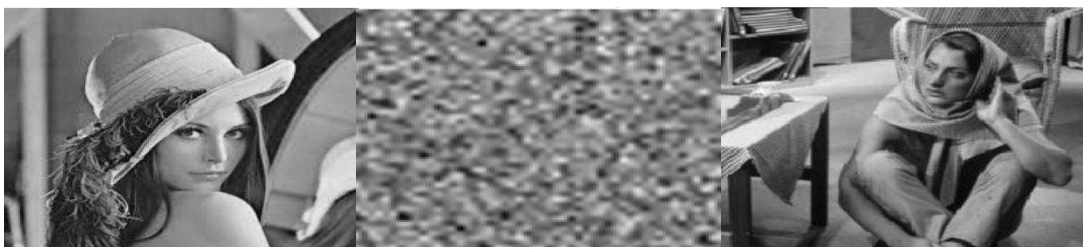

(a) (b) (c)

FIGURE 5 Image encryption (a) Hidden image (b) Binary bit planes (d) Encrypted image



(a) (b) (c) (d) (e)

FIGURE 6 Embedding process (a) Cover image (b) Edge pixels of cover image (c) Hidden image (d) Encrpted hidden image (e) Output Stego image



(a) (b) (c)

FIGURE 7 Extraction phase output (a) Received Stego image (b) Extracted hidden image (b) Decrypted hidden image

The distortion and similarity extent of an image can be quantified by Mean Square Error (MSE) to measure the reliability as given below:

$$MSE = \frac{1}{m}\sum_{i=C,S}^{m}\left(C - S\right)^2 \quad (28)$$

Where $m$ represents a total number of pixels in the cover image. $C$ and $S$ represent the cover and stego image respectively. The Peak Signal to Noise Ratio (PSNR) determines the statistical difference between the dynamic range of cover images and secret image invisibility. The PSNR can be expressed as follows:

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \quad (29)$$

The visual quality of the stego image can be measured by structural similarity (SSIM) measure [58]. This SSIM measure includes three distortion parameters namely, loss of correlation, luminance distortion, and contrast distortion. The SSIM is defined as:

$$SSIM(C,S) = \ell(C,S)\cdot\zeta(C,S)\cdot\delta(C,S) \quad (30)$$

$$\ell(C,S) = \frac{2\mu_C\mu_S + b_1}{\mu_C^2 + \mu_S^2 + b_1};\ \zeta(C,S) = \frac{2\sigma_C\sigma_S + b_2}{\sigma_C^2 + \sigma_S^2 + b_2};$$

$$\delta(C,S) = \frac{\sigma_{CS} + b_3}{\sigma_C\sigma_S + b_3} \quad (31)$$

Where, $\ell(C,S)$ represents the luminance function for measuring the proximity between mean luminance ( $\mu_C$ , $\mu_S$ ) of cover and stego images. $\zeta(C,S)$ represents the contrast function for measuring the proximity between the contrast of the two images. Here, the standard deviation $\sigma_C$ and $\sigma_S$ is used to measure the contrast. $\delta(C,S)$ represents the structural function for measuring the correlation coefficient between cover and stego images. $\sigma_{CS}$ represents the covariance between the images $C$ and $S$. $b_1$, $b_2$ and $b_3$ are positive constants.

The robustness of the proposed scheme can also be validated by Image fidelity [59] as given below:

$$IF = 1 - \frac{\sum_{i=0}^{M}\sum_{j=0}^{N}(C(i,j) - S(i,j))^2}{\sum_{i=0}^{M}\sum_{j=0}^{N}C(i,j)\times S(i,j)} \quad (32)$$

Table 1and Table 2 compares the stego image quality of the proposed method in terms of MSE, PSNR, SSIM, and IF with the existing methods namely Vernam Algorithm [37] and hybrid method of LSB Substitution, PVD, and EMD [51]. The proposed method gives a lesser MSE value because it alters less number of bits in each smooth pixel. Also, the perceptual stego image quality of the proposed method is proved by achieving higher image fidelity values.

### 4.2 PAYLOAD CAPACITY ANALYSIS

The volume of hidden data that can be embedded into the cover image without destructing the performance of the cover image is known as payload capacity. The payload capacity is generally represented by bits per pixel (bpp) unit.

$$\text{Payload Capacity} = \frac{\text{number of secret bits embedded}}{\text{Total no.of pixel in cover image}} \quad (33)$$

If the payload capacity is increased then, the PSNR value will drop significantly. Figure 8 compares the performance of the proposed steganography method for three different cover images by varying the payload capacity.

**Table 1**Stego image Quality analysis in terms of PSNR and MSE

| Cover image | Hidden Image | Vernam Algorithm[37] | | LSB+PVD+EMD[51] | | Proposed | |
|---|---|---|---|---|---|---|---|
| | | PSNR | MSE | PSNR | MSE | PSNR | MSE |
| Lena | Cameraman | 48.1323 | 0.9996 | 51.6375 | 0.4459 | 60.822 | 0.0537 |
| | Airplane | 47.0360 | 1.2866 | 50.2906 | 0.6081 | 57.727 | 0.1097 |
| | Barbara | 45.5886 | 1.7956 | 49.4191 | 0.7433 | 55.991 | 0.1636 |
| Bell Pepper | Cameraman | 48.5557 | 0.9067 | 51.8657 | 0.4231 | 60.760 | 0.0545 |
| | Airplane | 47.4486 | 1.1700 | 50.5187 | 0.5770 | 57.603 | 0.1129 |
| | Barbara | 45.9962 | 1.6347 | 49.6472 | 0.7052 | 55.907 | 0.1668 |
| Baboon | Cameraman | 44.0428 | 2.5632 | 54.0849 | 0.2538 | 60.773 | 0.0544 |
| | Airplane | 42.9645 | 3.2856 | 52.7379 | 0.3461 | 57.676 | 0.1110 |
| | Barbara | 41.4936 | 4.6101 | 51.8664 | 0.4230 | 55.937 | 0.1656 |

**Table 2**Stego image Quality analysis in terms of SSIM and MSE

| Cover image | Hidden Image | Vernam Algorithm[37] | | LSB+PVD+EMD[51] | | Proposed | |
|---|---|---|---|---|---|---|---|
| | | IF | SSIM | IF | SSIM | IF | SSIM |
| Lena | Cameraman | 0.759717 | 0.957373 | 0.957879 | 0.983574 | 0.999684 | 0.998022 |
| | Airplane | 0.758717 | 0.956223 | 0.956810 | 0.982574 | 0.999355 | 0.997489 |
| | Barbara | 0.757717 | 0.955183 | 0.955969 | 0.981574 | 0.999037 | 0.996948 |
| Bell Pepper | Cameraman | 0.768072 | 0.961408 | 0.961594 | 0.986040 | 0.999675 | 0.998079 |
| | Airplane | 0.767072 | 0.960260 | 0.960472 | 0.985032 | 0.999328 | 0.997535 |
| | Barbara | 0.766072 | 0.958989 | 0.959543 | 0.984402 | 0.999007 | 0.997169 |
| Baboon | Cameraman | 0.862774 | 0.946602 | 0.899530 | 0.987878 | 0.999679 | 0.999279 |
| | Airplane | 0.861775 | 0.945574 | 0.898802 | 0.986879 | 0.999347 | 0.999019 |
| | Barbara | 0.860774 | 0.944578 | 0.897695 | 0.985878 | 0.999024 | 0.998861 |

This figure shows that every steganography method will provide good quality stego image when the payload capacity is very low. However, the existing methods decrease the quality of the stego image while increasing the payload

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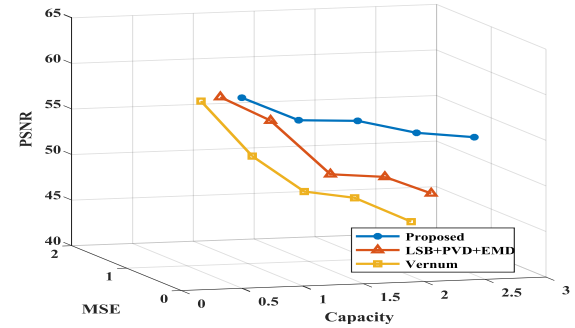
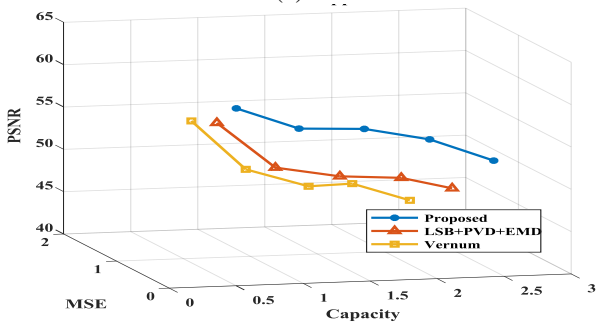
capacity. Instead, the quality of the stego image obtained by the proposed method is very high for all test cover images. In the meantime, the proposed scheme does not deteriorate the quality of the stego image while increasing payload capacity. If the payload capacity is increased to 2.5bpp then, the PSNR of the proposed method is higher than 52dB for all test cases. But, the PSNR of the existing methods is less than 47dB. Because the proposed scheme embeds the secret bits into both smooth region and edge region by setting different parameter values in the steganography embedding function. The edges are less affected by the changes after hiding secret data.

### 4.3 SECURITY ANALYSIS

In this section, the security of the proposed steganography scheme is measured using KL divergence [60]. This is the basic method for measuring the security of the steganography scheme because it exactly measures the difference between two distributions. Let $H_1$ and $H_2$ be the cover image histogram and stego image histogram respectively. The following expressions are used to estimate the K-L divergence from $H_1$ to $H_2$ and from $H_2$ to $H_1$

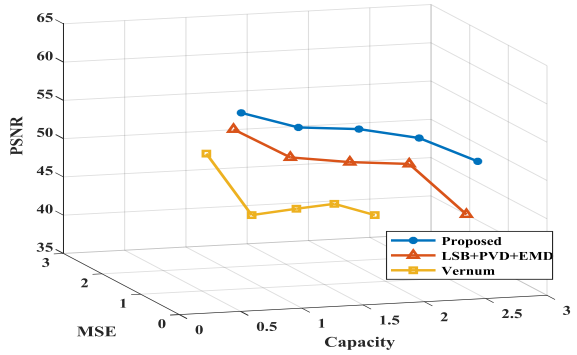



(a)




(b)

Here, $KLD_1$ and $KLD_2$ values are averaged to get the actual value of K-L divergence. When the stego image is as same as the cover image, the K-L divergence value will be equivalent to zero. In Figure 9, the security measure (KL divergence) value of the proposed steganography scheme is compared with the existing methods by varying the payload capacity.



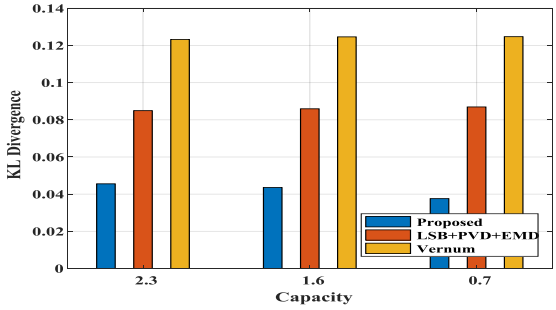

(c)

FIGURE 8 Payload capacity analysis for different cover images (a) Lena (b) Bell pepper (c) Baboon

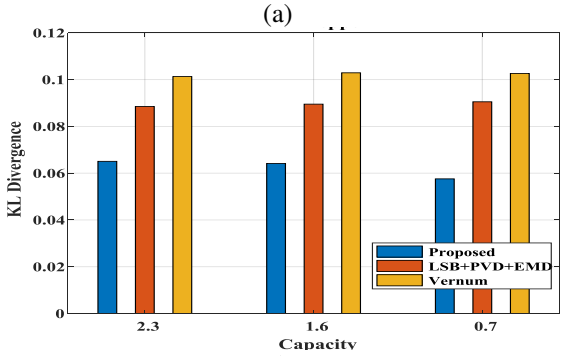
$$KLD_1 = \sum_{i=0}^{255} H_1(i) \times \log \frac{H_1(i)}{H_2(i)} \quad (34)$$

$$KLD_2 = \sum_{i=0}^{255} H_2(i) \times \log \frac{H_2(i)}{H_1(i)} \quad (35)$$

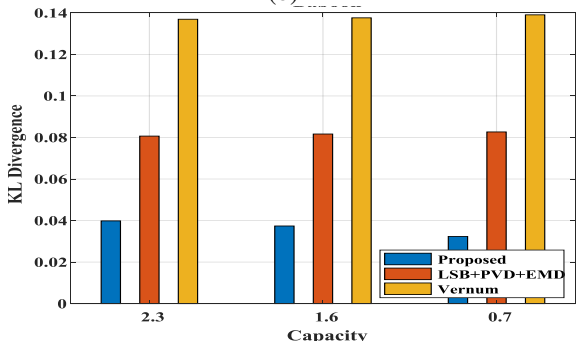
Figure 9 shows that the security level of the proposed method is higher than the existing methods while increasing the payload capacity from 0.7 to 2.3bpp.




(a)




(b)




(c)

FIGURE 9 Security measures for different cover images (a)Lena (b) Bell pepper (c) Baboon

This adaptive embedding process has been embedded in the secret image by selecting optimal parameters for smooth

and edge blocks. Thus, the overall security level of the proposed steganography scheme has been improved.

## 6. CONCLUSION

In this paper, a highly secured IoT protocol is utilized to transfer stego images to their destination and a secure and improved image quality steganography framework is proposed for the secure transmission of hidden images. This technique focused on image quality, payload capacity, and security of the image steganography method. The proposed SSOA optimized adaptive embedding method has selected suitable parameter values for edge and smooth blocks by determining the optimal threshold value for maintaining the high visual quality when the embedding density is high. The proposed edge/smooth block localization method provides much better results rather than using generic edge detection systems. In this paper, IoT is used to propose improved steganography as a method to improve medical data security, confidentiality, and integrity. When embedding additional data within medical images, medical image steganography requires extreme caution because the additional data must not degrade the image quality. In our proposed paper, the Internet of Things (IoT) scenario, combining encryption and steganography ensures secure and high-quality data transfer over the internet for medical image steganography. The experimental result also shows that the performance is much better in different perspectives like stego-image quality, payload capacity, and security. Thus, the stego images can't be detected by the unauthorized attacker and therefore the hidden secret image remains safe.

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