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Deep Adversarial Extreme Learning and Mises Regression Based Secure Quality Enhanced Satellite Image Transmission

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Abstract: Image compression and quality enhancement are two significant applications in the domain of digital image processing. Image compression aims to minimize the number of bits necessitated for digital representation of image whereas the objective of using quality enhancement is to improve the quality of compressed images that would have been compromised during the compression process of satellite image. Also with the swift evolution of communication network, the multimedia data with image and video increases exponentially, however transmission in an efficient and secure manner has become a paramount research topic. With the intent of improving security and enhancing the image quality during transmission, we propose a method called, Deep Gradient Adversarial Extreme Learning and MisesMarkovian Regression quality-enhanced secure image transmission (DGAEL-MMR) is proposed. The DGAEL-MMR method is split into two sections, namely, image compression and quality enhancement for secure transmission. First with the satellite images provided as input, Deep learning model called, Stochastic Gradient Generative Adversarial Network and Extreme Image Compression is proposed to ensure the security of satellite images by maintaining their confidentiality and integrity. Second to enhance the quality of compressed satellite images, Bernstein–von MisesMarkovian Kernel Regression Optimization-based model is applied. This proposed DGAEL-MMR method aims to boost the security of satellite images during their transmission across networks. Quality enhancement parameters like Peak Signal to Noise Ratio (PSNR), Bit Error Rate (BER) and security parameters like confidentiality and integrity are used to assess and compare the performances of the method. Obtained results show that the DGAEL-MMR method performs better than the conventional methods both in terms of the security (i.e., data confidentiality by 16% and data integrity by 20%) parameters and quality enhancement (i.e., PSNR by 26%) mentioned above.

Keywords: *Compression, Bernstein–von Mises, Markovian Kernel Regression, Stochastic Gradient Generative Adversarial Network, Extreme Image Compression*

1. Introduction

As far as image compression in digital cameras is concerned, compression is initially performed prior to quality enhancement. An Auto Encoder (AE) deep learning-based compression method was proposed in [1] for performing lossy image compression. Bu quality measurement between the original and a compressed image, the Peak Signal to Noise Ratio and Bit Error Rate involved in compression for secure transmission was not analyzed.

To handle this challenge, a simultaneous mechanism of compression and encryption without influence the efficiency of each other processes employing Burrows-Wheeler Transform [2] was proposed Despite improvements observed in terms of security aspects, the quality enhancement was not focused.

To address the above said issues, in this work, a hybrid method called Deep Gradient Adversarial Extreme Learning and MisesMarkovian Regression (DGAEL-MMR) combining secure quality enhanced data transmission of satellite images is proposed.

- To secure quality enhanced data transmission of satellite images, DGAEL-MMR method is proposed. The WSSR-CDC method is introduced with the application of the secured compression-based data transmission and quality enhanced data transmission on contrary to existing work that used either data transmission or quality enhancement across the images.
- To improve confidentiality and integrity of satellite images, Deep Stochastic Gradient Generative Adversarial Network and Extreme Image Compression-based secure data transmission model is introduced that with the aid of Stochastic Gradient Generative Adversarial Network aids in reducing the modification and therefore improving the images to the intended recipient.
- To improve PSNR and BER employing Bernstein–von MisesMarkovian Kernel Regression Optimization-based perceptual quality enhancement algorithm.

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- The performance are evaluated through extensive simulations with the UC Merced Land Use Dataset are validated with the state-of-the-art methods.

2. Related works

In this section, a detailed review on the compression-based data transmission mechanism and methods employed for quality enhanced secure data transmission based on the various compression methods and quality enhancement methods are presented.

2.1 Secure satellite image compression-based data transmission mechanisms

Image data play pivotal character in several real-time involving both online and offline applications. Moreover, in almost all the field imaging system has been found a major place in diagnosing disease, identifying abnormalities for surveillance using satellite images to name a few. The satellite imaging data contain both huge and sensitive information which requires huge storage space and specialized security mechanism are required while transmitting the same. Also during transmission, malicious users can attack the communication channel and obtain the sensitive information. In [3], a hybrid method involving, wavelet confusion and diffusion were applied for image compression process. However is said to encounter security concerns during data acquisition, processing, and transmission stages. In [4], a generic post-quantum method named the PyHENet that specifically integrated cryptography with plaintext deep learning was proposed for ensuring accurate transmission was proposed. Yet another aggression compression algorithm focusing on the timeliness of transmission was presented in [5]. To address the above-mentioned gap, a data governance method taking into consideration pertinent handling of data and sharing mechanisms to ensure minimize risks of sensitive information leakage was presented in [6]. Yet another compression mechanism employing deep learning for medical images was designed in [7].A digital image processing review of deep learning techniques for secure transmission was investigated in [8].A compressive sensing mechanism employing fine tunable gradient Hopfield neural network to focus on security aspects involved in transmitting images was applied in [9]. Yet another secure cloud based image architecture, to focus on the medical image processing employing deep learning network to focus on security aspect was designed in [10]. However the PSNR and BER factors involved in secure transmission was not addressed. To address on this gap, block luminance and DL were applied in [11] to address performance evaluation factors into concern. However, the Internet is a very highly susceptible medium with many security gaps. Logistic map with deep neural network to focus both on the security and quality aspects were designed in [12]. Ant Lion Optimization (ALO) and Diffie–Hellman-based Two fish cryptography (DHT) were combined in [13] to ensure secure transmission of images. However, the transmission error ratio was not included. To concentrate on this aspect, unsupervised variational encoder was applied in [14]. Yet another method ensuring secure transmission using deep neural network and RSA algorithm was proposed in [15]. An energy efficient data transmission method employing splindle convolutional auto encoder was presented in [16].

Table 1 Summary of research gaps on secure satellite image compression-based data transmission mechanisms

Referen ces	Metho dology	Secure compr ession based data transm ission	Qualit y enhanc ement	Parame ter improv ed	Drawb acks
(Salam Fr et al. 2023)	(AE) deep learnin g-based compr ession metho d	Stacke d Auto Encod er	Nil	Reconst ruction accurac y, SSIM	Peak Signal to Noise Ratio and Bit Error Rate involve d in compre ssion for secure transmi ssion was not analyze d
(Qian Chen et al. 2023)	PyHE Net	Nil	combi nes crypto graphy with plainte xt deep learnin g librari es	Accura cy	Secure transmi ssion was not ensured
(Isaac Shiria et al. 2024)	PRIMI S	Deep Sparsif ying Transf	Nil	Securit y	Despite improv ement observe

		orm Learning			d in confidentiality however integrity of images was not focused
(MayadaKhairy et al. 2022)	DLBL	Block luminance adopting deep learning	Nil	Compression ratio, PSNR and SSIM	Security aspects involving integrity was not focused
(Abdulmohsen Almalawi1 et al. 2024)	hybrid cryptographic mechanism	Ant Lion Optimization (ALO) and Diffie–Hellman-based Twofish cryptography (DHT)	Nil	High accuracy, low time consumption and delay	Integrity factor was not addressed

2.2 Quality enhanced secure data transmission mechanisms

Despite utilization of satellites image for earth observations, they are currently both laborious and cumbersome due to compromising of quality during compression. Also images acquired at large scale possess the potential to extensive enhance resolution, both spatial coverage and temporal frequency towards quality enhancement.

Two deep learning methods were applied in [17] for improving resolution in terms of quality. Yet another method employing hybrid fitness function was presented in [18] .However, the bit error rate involved in transmission was not focused. To address on this issue, ensemble, forest and boosting methods were applied in [19]. To overcome this issue, a method called Self-Fuse Net, specifically for tremendously poor-resolution satellite images was proposed in [20]. To improve the visual perception an improved technique was proposed in [21]. Yet another novel local global fusion model with SAR) was presented in [22]. A super resolution method focusing on the good tradeoff between consistency and synthesis characteristics was proposed in [23]. A novel method using deep learning as a proxy was presented in [24] .An elaborate investigation concerning several image enhancement techniques using deep learning was proposed in [25]. Yet another method to enhance the contrast of image during transmission employing optimization method called, improved Particle Swarm Optimization was presented in [26]. lso low contrast satellite images were improved using an integration model called, Lifting Haar wavelet Transform and Singular Value Decomposition [27]. A satellite image enhancement method employing deep learning to focus on the PSNR and SSM was presented in [28]. However the above said methods did not focus on the transmission aspect. To address on this gap, a fusion of neural network and genetic algorithm was proposed in [29]. By employing this fusion mechanism quality classification was improved in terms of MSE. Histogram and nonlinear functions were applied in [30] to enhance contrast of satellite images during transmission.

Table 2 Summary of research gaps on quality enhanced data transmission methods

References	Methodology	Secure compression based data transmission	Quality enhancement	Parameter improved	Drawbacks
(Baritha Begum et al. 2023)	Burrows-Wheeler Transform		Burrows-Wheeler Transform	Ensured security	Quality aspects were not focused
(Lavanya Sharma et al. 2020)	Improved technique	Nil	Entropy and histogram Analysis	MSE	Bit error rate was not analyzed
(Pau Gallés et al. 2024)	IQUAFLOW	Nil	Deep learning task as a proxy	SSIM and PSNR	Bit error rate was not focused

(Xiaowen Zhang et al. 2023)	improved particle swarm optimization algorithm	Nil	Contrast enhancement	Minimal running time	Bit error rate was not analyzed
(Trong-An Bui et al. 2024)	edge-computing-enabled inference model	Nil	Deep learning approach	PSNR and SSIM	Bit error rate was not included

3. Problem methodology and system model

3.1 Problem methodology

Auto Encoder (AE) deep learning-based compression [1] presented a novel and robust lightweight image compression method with the objective of compressing and decompressing images without explicitly processing their content. Also to perform quality enhancement lightweight binary filter was applied to the input image with the objective of enhancing the overall image reconstruction process. Next, the image classifier employing CNN also determined which pre-trained Stack Auto Encoder was utilized for compressing and decompressing the image on the basis of its content itself. This technique had the advantage of training very large single SAE model that can compress and decompress any image irrespective of its content. Though several advantages like, improved compression rate the security aspects like, confidentiality and integrity of compressed images were not handled. In [2], a two-step scrambling procedure boosting the security of input images prior to the application before applying the Burrows-Wheeler Transform was proposed. Here, a unique key was generated initially and then Burrows-Wheeler Transform (BWT) was applied for improving the overall compression process. The output of the compressed images was then passed to encode using Move-To-Front Transform encoder. This in turn ensured secure image transmission. However, the quality measurement performance metrics like, the Peak Signal to Noise Ratio and Bit Error Rate involved in compression was not analyzed owing to the lack of separate resource efficient blind quality enhancement model. To address on these gaps, in this work, DGAEL-MMR secure image transmission for satellite image using desnoising and compression is proposed. The main objective of our proposed DGAEL-MMR is given below.

- A hybrid secured compression and quality enhanced data transmission method for satellite images are proposed.
- To boost confidentiality and integrity of satellite images, Deep Stochastic Gradient Generative Adversarial Network and Extreme Image Compression-based secure data transmission algorithm is designed.
- To improve PSNR and BER, a model called, Bernstein–von MisesMarkovian Kernel Regression Optimization-based quality enhancement model employing Bernstein–von Mises and Kernel Regression function is designed.
- Extensive experiments are organized to explore the impact of numerous performance metrics like, PSNR, BER, confidentiality and integrity on how well the method performs, issuing perceptions to into the application for training optimization and deep learning algorithms for data transmission.

3.2 System design

A hybrid secured quality enhanced compressed algorithms using Deep Gradient Adversarial Extreme Learning and MisesMarkovian Regression quality-enhanced (DGAEL-MMR) meeting the objectives of both secure data transmission and quality enhancement involving satellite images is detailed. Figure 1 shows the structure of secured data transmission model where the input images obtained from UC Merced Land Use Dataset are provided as input to the extreme learning. In the hidden layer, the Stochastic Gradient Generative Adversarial Network is applied that performs the tasks of compression by means of encoder and quantizer. To perform secure data transmission the decoder or generator checks and validates the authenticity by using random key generated separately for each session. Upon successful validation secure transmission is ensured and on contrary the process is continued with other set of generators. Figure 2 shows the structure of Bernstein–von MisesMarkovian Kernel Regression Optimization-based perceptual quality enhancement model. In the first part, initially, the compressed satellite images are subjected to two statistical functions, namely mean and standard deviation for achieving finer details. Next, perceptual quality operation both forming the forward process and the reverse process employing Bernstein–von is generated. Finally Kernel Regression function is applied to obtain the optimized quality enhanced images for secure data transmission.

4 Proposed methodology

In this section, an elaborate description of the proposed method Deep Gradient Adversarial Extreme Learning and MisesMarkovian Regression quality-enhanced secure image transmission (DGAEL-MMR) is detailed. First the working structure of Deep Stochastic Gradient Generative Adversarial Network and Extreme Image Compression-based secure data transmission for satellite image is provided. Second, the working structure of quality enhancement of compressed images using Bernstein–von MisesMarkovian Kernel Regression Optimization is detailed.

4.1 Deep Stochastic Gradient Generative Adversarial Network and Extreme Image Compression-based secure data transmission

Satellite imagery across sectors is a crucial element of surveillance, investigation, crime scene analysis, enabling the transfer of satellite images between extensively dense locations to display important information regarding criminal pursuits happening globally. But, the transmission of satellite images across public networks can result in various security issues, including those related to integrity, and confidentiality. The proposed Deep Stochastic Generative Adversarial Network and Extreme Image Compression-based secure data transmission aims to enhance the security of satellite images during their transmission across public networks. The proposed Deep Stochastic Gradient Generative Adversarial Network and Extreme Image Compression-based secure data transmission model in our work is viewed as a combination of conditional Generative Adversarial Network and fine-tuned bit rate via Extreme learned compression. The proposed model with the input as 'SI' for compression involved two processes, namely, fine-tuned weight improved Extreme Image Compression and Deep Stochastic Gradient Generative Adversarial Network. Figure 1 shows the block diagram of Deep Stochastic Gradient Generative Adversarial Network and Extreme Image Compression-based secure data transmission model.

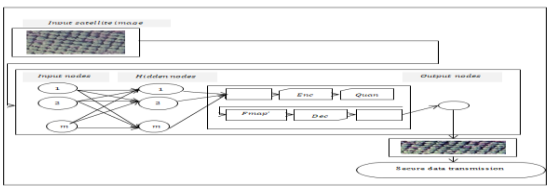

Figure 1 Block diagram of Deep Stochastic Gradient Generative Adversarial Network and Extreme Image Compression-based secure data transmission

As illustrated in the above figure with the objective of designing a secure data transmission of satellite images, the input sample images obtained from UC Merced Land Use Dataset forms the input to the extreme learning. Here, in the hidden layer, or the hidden nodes in the hidden layer are subjected to the Deep Stochastic Gradient Generative Adversarial Network where with the encoder 'Enc' and quantizer '$Quan$' the sample input image 'SI' is compressed '$Fmap'$'. The decoder 'Dec', with the aid of random key generated by discriminator checks for authenticity and upon successful comparison proceed with data transmission. On contrary the process is said to be proceeded with other set of generators. With single hidden layer of Extreme Learning (EL) employed in our work, suppose that the output function of the '$i-th$' hidden node is '$h_i(SI) = G(p_i, q_i, SI)$', where '$p_i$' and '$q_i$' forms the pixel of sample input image 'SI'. Then, the output function of EL for single hidden layer with 'L' hidden nodes (i.e., sample input images) is mathematically represented as given below.

$$f_L(SI) = \sum_{i=1}^{L} w_i h_i SI \quad (1)$$

From equation (1), 'w_i' represent the output fine-tuned weight of the 'i' hidden node (i.e., sample input image). The output fine-tuned weight of the 'i' hidden node is mathematically represented as given below.

$$W_i(n) = \sum_{i=1}^{n} w_{i+1} SI_i(n-1) \quad (2)$$

By applying the above said fine-tuned weight, controls the flow of data (i.e., satellite image being received from transmission) within network. In addition 'h_i' forms hidden layer output mapping of EL formulated as below.

$$h(SI) = [h_1(SI), h_2(SI), \dots, h_L(SI)] \quad (3)$$

Based on above formulation (3), the hidden layer output matrix 'H' is given as below.

$$H = \begin{bmatrix} h(SI_1) \\ h(SI_2) \\ \dots \\ h(SI_m) \end{bmatrix} = \begin{bmatrix} G(p_1, q_1, SI_1) & \dots & G(p_L, q_L, SI_1) \\ G(p_1, q_1, SI_2) & \dots & G(p_L, q_L, SI_2) \\ \dots & \dots & \dots \\ G(p_1, q_1, SI_m) & \dots & G(p_L, q_L, SI_m) \end{bmatrix} \quad (4)$$

Then, above hidden layer output mapping is subjected to Stochastic Gradient Generative Adversarial Network. The proposed Stochastic Gradient Generative Adversarial Network for compression to be performed at the hidden layer output mapping involves three components, namely, encoder 'Enc', decoder 'Dec' and a quantizer '$Quan$'. The discriminator 'D' (i.e., admin) generates a random key for each generator 'G' (i.e., the source sender sample image) to assess the authenticity of the receiver in need of the image. This random key 'RK' is generated by the discriminator 'D' and differs according to each session. The encoder 'Enc' maps the quality enhanced optimized image 'opt' to a feature map '$Fmap$' whose values are quantized in the hidden layer of extreme learning to obtain a compressed representation as give below.

$$\text{'}CI = Fmap' = Quan\big(Enc(SI)\big)\text{'} \quad (5)$$

On the other hand, the decoder recovers the image via reconstruction map as given below.

$$SI' = Dec(Fmap') \quad (6)$$

Then, average number of bit required for encoding '$Fmap'$' is evaluated by the entropy '$H(Fmap')$'. Followed by which the rate distortion trade-off between reconstruction quality and bit-rate optimization is formulated via Stochastic Gradient function as given below.

$$RD = Enc[loss(SI, SI')] + W_i(n)H(Fmap') \tag{7}$$

$$W = W_i - \frac{\eta}{n}\sum_{i=1}^{n} \nabla RD_i \tag{8}$$

From equation (7), '$loss$' refers to loss function that evaluates how intuitively homogeneous 'SI'' is to 'SI'. Moreover, '$W_i(n)$' refers to the control of flow of data or satellite images (i.e., bit-rate optimization) obtained via fine-tuning of weight with respect to entropy '$H(Fmap')$'. By applying Stochastic Gradient function for obtaining the fine-tuned weight in hidden layer of EL secure transmission is ensured between generator and receiver via discriminator.

Input: Dataset 'DS', Satellite (i.e., sample) Image '$SI = \{SI_1, SI_2, \ldots, SI_n\}$'

Output: secure data (i.e., image) transmission

Step 1: **Initialize** 'n', '$\eta = 0.5$'

Step 2: **Begin**

Step 3: **For** each Dataset 'DS'

//Extreme learning of optimized image

Step 4: Formulate output function of EL for single hidden layer with 'L' hidden nodes as given in equation (1)

Step 5: Fine-tune weight as given in equation (2)

Step 6: Formulate hidden layer output mapping of EL as given in equation (3) for single sample image

Step 7: Formulate hidden layer output mapping of EL as given in equation (4) for 'n' sample images

//Stochastic Gradient GAN

Step 8: Obtain random key 'RK' for each generator

Step 9: Obtain compressed form as given in equation (5)

Step 10: Obtain reconstructed map as given in equation (6)

Step 11: Evaluate rate distortion trade-off between reconstruction quality and bit-rate optimization as given in equations (7) and (8)

Step 12: Obtain key 'RK'' from receiver

Step 13: **If** '$RK = RK'$'

Step 14: **Then** receiver is genuine

Step 15: Secure data transmission between generator and receiver

Step 16: **Else**

Step 17: Receiver is not genuine

Step 18: Proceed with other set of generator and receiver

Step 19: **End if**

Step 20: **End for**

Step 21: **End**

Algorithm 1 Deep Stochastic Gradient Generative Adversarial Network and Extreme Image Compression-based secure data transmission

As given in the above algorithm with the objective of improving confidentiality and integrity of satellite images being transmitted between users (i.e., generator and user), first extreme learning for the input sample image is subjected to hidden layer where fine-tuning of weight is performed to control flow of data being compressed by the discriminator. In this manner data confidentiality is said to be ensured. Next, the hidden layer output mapping is subjected to Stochastic Gradient Generative Adversarial Network. Finally, authenticity of generator is ensured via Stochastic Gradient GAN using random key generated by the discriminator. Followed by which compression is performed upon successful authenticity and on contrary is subjected to other set of generators. With this the integrity is said to be improved.

4.2 Bernstein–von MisesMarkovian Kernel Regression Optimization-based perceptual quality enhancement

One of the preliminary issues in the area of secure satellite image processing and transmission is quality enhancement, where the principal aim is to enhance the visual quality of the compressed image. Digital image devices have various scopes of applications, such as weather forecasting, landscape analysis environmental assessment and so on. During satellite image data transmission and compression processes, sufficient compression ratio is not provided therefore compromising the image quality or degrading the quality of compressed image. Hence, compression and quality enhancement are said to be inseparable due to the reason that the higher the compression ratio more data is said to be packet into a smaller space therefore minimizing the overall quality of the compressed image.

Compressed image quality enhancement during transmission may be given rise by numerous intrinsic and extrinsic circumstances that are frequently not probable in practical circumstances. Hence, quality enhancement of compressed images during transmission plays a significant part in an extensive applications range. Though several materials and methods have been proposed for enhancing quality of compressed images during transmission, the issue of perceptual quality remains an open issue, especially in situations extracted from large images.

Recently, there has been a plethora of optimization based models suggested for enhancing quality of satellite images during transmission. In this work, an alternative model to the issue of perceptual quality enhancement based on Gaussian Markovian Kernel Regression optimization via Posterior Distribution is proposed. By formulating the problem as a Gaussian Markovian Kernel Regression optimization and taking a Bernstein–von Mises theorem to solving this issue, perceptual quality enhancement model dynamically fine-tunes principal image and perceptual statistics in a flexible manner to provide high quality performance improvement (i.e., improving PSNR) while maintaining relatively low computational complexity (i.e., training time and bit error rate).

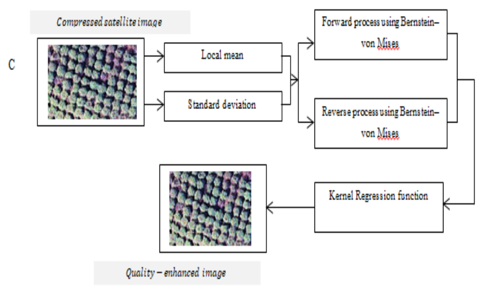

Figure 2 Block diagram of Bernstein–von MisesMarkovian Kernel Regression Optimization-based perceptual quality enhancement model

As illustrated in the above figure, with the compressed satellite images obtained from the above section are subjected to perceptual quality enhancement using a combination of Bernstein–von Mises and Kernel Regression function. Perceptual quality enhancement is the second significant step where it itself gets implemented on the compressed satellite image. The function of this perceptual quality enhancement step is designed to abstract data in dispersed manner and then ascertains to reverse the dispersion process to generate the design satellite image data samples from the compressed image.

The function of this perceptual quality enhancement step is designed with the purpose of computing and making use of compressed satellite image-dependent, locally varying via local mean and standard deviation, masking thresholds via forward and reverse process to adapt the regression function to the varying characteristics of the visual data. The forward and reverse process with the mean and standard deviated results is generated using the Bernstein–von Mises function. Finally, to produce quality enhanced satellite image data Kernel Regression function is applied. Under perceptual quality enhancement functions, an expression for both local mean and the standard deviation for the satellite (i.e., sample) image of size '$n * n$' is produced as given below.

$$\mu(p,q) = \frac{1}{n*n}\sum_{p=1}^{n}\sum_{q=1}^{n} f(p,q) \tag{9}$$

$$\sigma = \sqrt{\frac{1}{n*n}\sum_{p=1}^{n}\sum_{q=1}^{n}\left(f(p,q) - \mu(p,q)\right)^2} \tag{10}$$

From the above equations (9) and (10) with the aid of the mean '$\mu(p,q)$' and the standard deviation 'σ' average of these given compressed image 'CI' values for achieving finer details are obtained with the aid of Gaussian dispersion process. Perceptual quality enhancement model learn the training data distribution '$p(CI_0)$by performing Gaussian Markovian process. The perceptual quality enhancement process comprises of a forward and a reverse process. In the forward process, Gaussian Markovian function is added to the compressed satellite image to the clean image '$CI_0 \sim p(CI_0)$'. Then, the quality enhancement operation at each time instance 't' in the forward process using Bernstein–von is formulated as given below.

$$\epsilon(CI_t|CI_{t-1}) = X = N\left(CI_t, \sqrt{\alpha_t}CI_{t-1}, (1-\alpha_t)QEI\right) \tag{11}$$

From the above equation (11) '$CI_1, CI_2, \dots, CI_t$' and '$\alpha_1, \alpha_2, \dots, \alpha_t$' represents the Gaussian Markovian chain of compressed images and the perceptual factor for each compressed images with the resultant stored in quality enhanced image 'QEI' (i.e., intermediate results). Followed by which the posterior distribution or reverse process with the purpose of optimizing the image PSNR during quality enhancement using Bernstein–von is formulated as given below.

$$\epsilon(CI_{t-1}|CI_t, CI_0) = Y = N(CI_{t-1}, \mu, \sigma^2, QEI) \tag{12}$$

$$\mu(CI_t, CI_0) = \frac{\sqrt{\alpha_{t-1}}(1-\alpha_t)}{1-\alpha_t}CI_0 + \frac{\sqrt{\alpha_t}(1-\alpha_t-1)}{1-\alpha_t}CI_t \tag{13}$$

From the above equations (12) and (13), a series of negligible perceptual factors is performed using the Kernel Regression function to obtain back the quality enhanced satellite image.

Finally, Kernel Regression function is applied with the purpose of identifying the noiseless pixel value with respect to the pixel coordinates in the satellite image. In other words, the variation in one pixel based on another pixel is evaluated. Then to obtain the quality enhanced image Kernel Regression function is applied to the 'X' with smoothing parameter 'δ' (selected in such a manner so as to become smaller as the volume of training sample image increase via '$k-th$' nearest training instance) in three spatial directions to arrive at median filtered values. This is mathematically formulated as given below.

$$f_0(X) = f_0(X_{11}, X_{12}, X_{13}) = \frac{1}{\pi^3\delta^3}\exp\left(-\frac{X_{11}^2+X_{12}^2+X_{13}^2}{\delta^2}\right) \quad (14)$$

Finally, to improve quality enhanced data transmission the optimization formula is mathematically stated using Kernel Regression function as given below.

$$opt = argmin\ (X - PI_i b)_{W_i}^2 \quad (15)$$

$$W_i = diag\ [k_1(X_1)k_1(PI_1 - PI), \ldots, k_m(X_m)k_m(PI_m - PI)] \quad (16)$$

$$PI_i = \begin{bmatrix} 1 & (PI_1 - PI)^T & mat((PI_1 - PI)(PI_1 - PI)^T) & .. \\ 1 & (PI_2 - PI)^T & mat((PI_2 - PI)(PI_2 - PI)^T) & .. \\ .. & .. & .. & .. \\ 1 & (PI_m - PI)^T & mat((PI_m - PI)(PI_m - PI)^T) & .. \end{bmatrix} \quad (17)$$

From the above equations (15), (16) and (17) the optimized quality enhanced resultant satellite image 'opt' is obtained based on the diagonal matrix 'W_i', perceptualised samples '$X = (X_1, X_2, \ldots\ldots X_m)$' and number of pixels in neighborhood of position 'PI' respectively via 'mat'. By using this pixel in neighborhood of position via Kernel Regression function optimized quality enhanced images are retrieved.

Input: Dataset 'DS', Compressed Image '$CI = \{CI_1, CI_2, \ldots, CI_m\}$'

Output: optimized quality enhanced satellite images

Step 1: **Initialize** 'n', coordinates 'p, q'

Step 2: **Begin**

Step 3: **For** each Dataset 'DS' with Compressed Image 'CI'

Step 4: Evaluate local mean and the standard deviation for the satellite (i.e., sample) image of size '$n * n$' as given in equations (9) and (10)

Step 5: Perform perceptual quality enhancement using Bernstein–von as given in equations (11), (12) and (13)

Step 6: Obtain median filtered values via three spatial directions as given in equation (14)

Step 7: Obtain quality enhanced image Kernel Regression function using equation (15), (16) and (17)

Step 8: Return quality enhanced optimized image 'opt'

Step 9: **End for**

Step 10: **End**

Algorithm 2 Bernstein–von MisesMarkovian Kernel Regression Optimized quality enhancement

As given in the above algorithm with the objective of enhancing the quality of compressed images during transmission of satellite images, the compressed images are subjected to local mean and standard deviation for achieving finer details. Next, perceptual quality enhancement process using Bernstein–von function is applied to the finer details so as to optimize PSNR. Finally, median filtered values via three spatial directions are subjected to Kernel Regression function for obtaining quality enhanced optimized output with minimal bit error rate.

5 Results and discussion

In this section, we validate the proposed Deep Gradient Adversarial Extreme Learning and MisesMarkovian Regression quality-enhanced secure image transmission (DGAEL-MMR) for different performance metrics. An in-depth comparison is also made with two existing methods AutoEncoder (AE) deep learning-based compression [1] and Burrows-Wheeler Transform [2] by implementing using Python high-level general-purpose programming language. The dataset used in this work is UC Merced Land Use Dataset extracted from http://weegee.vision.ucmerced.edu/datasets/landuse.html. The entire experiment is performed in an Intel Core i5-6200U CPU @ 2.30GHz 4 cores with 4 Gigabytes of DDR4 RAM.

5.1 Dataset description

The satellite image dataset employed in our work for performing secured quality enhanced compressed satellite image transmission is UC Merced Land Use Dataset extracted from http://weegee.vision.ucmerced.edu/datasets/landuse.html. The UC Merced Land Use Dataset is a 21 class land use image dataset specifically employed for conducting research. The dataset includes 100 images for each of the distinct classes, to name a few being, agricultural, airplane, baseball diamond, beach, buildings, chaparral and so on. Each image in the dataset measures 256x256 pixels. Moreover, the images were extracted manually from the USGS National Map Urban Area Imagery collection for various urban areas globally and the pixel resolution is 1 foot.

5.2 Performance analysis of secure satellite image data transmission in terms of data confidentiality and data integrity

While designing model for secure image data transmission, one of the most signfiicant performance metric is the data confidentialiy. The data confidentilaity rate is referred to as the percentage ratio of the number of sample images that are received by the authorized receiver and is mathematically stated as given below:

$$DC = \sum_{i=1}^{n} \frac{Samples_{IR}}{Samples_i} * 100 \quad (18)$$

From the above equation (18), data confidentiality 'DC' is estimated by taking into account the sample data involved in the simulation '$Samples_i$' and the sample instances received to the intended recipient '$Samples_{IR}$'. It is measured in terms of percentage. Next, to validate and analyze whether secure image data transmission is ensured for the given satellite images, data integrity is evaluated. Data integrity is measured as the percentage ratio of sample images that are not altered by any users to the overall sample images provided as input. The data integrity is mathematically formulated as given below.

$$DI = \sum_{i=1}^{M} \frac{Samples_{NA}}{Samples_i} * 100 \quad (19)$$

From the above equation (19) the data integrity 'DI' is measured by considering the sample images taken for simulation '$Samples_i$' and the number of sample compressed images not altered by any malicious users '$Samples_{NA}$'. Figure 3 and figure 4 shows the simulation results of compressed based secured data transmission using (a) noisy image, (b) (b) Auto Encoder (AE) deep learning-based compression [1] (c) burrows-wheeler transform [2] and (d) proposed DGAEL-MMR method with respect to agricultural and building area image.

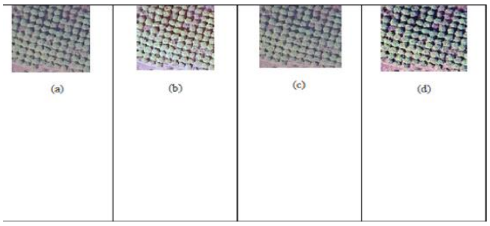

Figure 3 Simulation results of compressed based secured data transmission in agricultural area image (a) noisy input (b) Auto Encoder (AE) deep learning-based compression [1] (c) burrows-wheeler transform [2] (d) proposed DGAEL-MMR method

Figure 4 Simulation results of compressed based secured data transmission in building area image (a) noisy input (b) Auto Encoder (AE) deep learning-based compression [1] (c) burrows-wheeler transform [2] (d) proposed DGAEL-MMR method

From above simulation results it is inferred that compression being performed well using proposed DGAEL-MMR method, secured transmission is said to be ensured. Table 3 below provides the tabulation results of data confidentiality and data integrity measured by substituting the values in equations (18) and (19) for two existing methods, AE deep learning-based compression [1], burrows-wheeler transform [2] and proposed DGAEL-MMR.

Table 3 Tabulation of data confidentiality and data integrity using DGAEL-MMR, AE deep learning-based compression [1] and burrows-wheeler transform [2]

	Data confidentiality (%)			Data integrity (%)		
Sample images	DGAEL-MMR	AE deep learning-based compression	burrows-wheeler transform	DGAEL-MMR	AE deep learning-based compression	burrows-wheeler transform
150	95.33	92.66	91.33	97.33	94.66	93.33
300	91.15	88.15	85.15	95.15	91.55	87.55
450	90.35	86.35	83.25	93.15	88.35	84.15
600	88.15	84.25	80.45	90.45	85.25	80.25
750	90.35	86.15	82.35	88.15	81.35	76.35
900	92.15	87.35	83.15	85.35	78.45	74.15
1050	94.55	88.25	85.35	88.25	80.35	76.35
1200	92.15	85.35	80.25	90.45	83.15	79
1350	93.15	86.35	82.15	92.15	85.35	80.35
1500	90	84.15	80.15	90	82	75.35

From the above tabulation results is inferred that with increased sample image neither increase nor decrease in data confidentiality or data integrity is found. The reason is that the size of agricultural and building images differs for different sample images and hence variation is observed in the resultant confidentiality and integrity aspects also. This is evident from the simulation results with 150 sample images provided as input, sample instances received to the intended recipient using DGAEL-MMR to be 142, 138 using [1] and 136 using [2]. With this result the overall data confidentiality using the three methods were observed to be 95.33%, 92.66% and 91.33% respectively. This confirms the results that the data confidentiality using proposed DGAEL-MMR method is found to be comparatively better than [1] and [2]. In a similar manner, with 150 sample images provided as input, number of sample compressed images not altered by any malicious users using DGAEL-MMR to be 145, 141 using [1] and 139 using [2], the data integrity were observed to be 97.33%, 94.66% and 93.33% respectively. This in turn corroborates the objective of enhancing data integrity using the proposed DGAEL-MMR method. With 10 set of iterations performed with distinct class of 1500 images, the data confidentiality using proposed DGAEL-MMR method was improved by 6% compared to [1] and 10% compared to [2]. In a similar manner, the data integrity using DGAEL-MMR method was found to be improved by 7% compared to [1] and 13% compared to [2].

5.3 Performance analysis of quality enhanced secure data transmission in terms of PSNR and Bit Error Rate

In this section to validate and analyze the results of quality enhancement, in our work PSNR and BER is employed. Peak Signal to Noise Ratio (PSNR) is defined as the ratio between maximum possible power of the signal and the power of the noise.

$$PSNR = 10\left(log_{10}\left(\frac{255}{\sqrt{MSE}}\right)\right) \qquad (20)$$

The mean squared error 'MSE' from the above equation (20) measures the average of the squares of the errors as given below.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(act - obs)^2 \qquad (21)$$

From the above equations (20) and (21), the PSNR '$PSNR$' is measured based on the actual image '$SI(p,q)$' transmitted between users and the distorted image (i.e., quality compromised pixel) '$b(i,j)$' respectively measured for ensuring secured quality enhanced data transmission as a factor. On the other hand, the bit error rate (BER) is referred to as the number of bit errors measured for a specific compressed image per unit time. To be more specific, the BER is measured as the number of bit errors (i.e., compressed image at receiving end) divided by the total number of transferred bits (i.e., compressed image at sending end) during a specified time interval.

$$BER = \frac{BE_{recv}}{B_{transf}} * 100 \qquad (22)$$

From the above equation (22), bit error rate 'BER' is measured based on the bits transferred 'B_{transf}' and the number of bit error occurred 'BE_{recv}'. It is measured in terms of percentage. Figure 5 and figure 6 shows the simulation results of quality enhanced secured data transmission using (a) noisy image, (b) (b) Auto Encoder (AE) deep learning-based compression [1] (c) burrows-wheeler transform [2] and (d) proposed DGAEL-MMR method for agricultural and building area image.

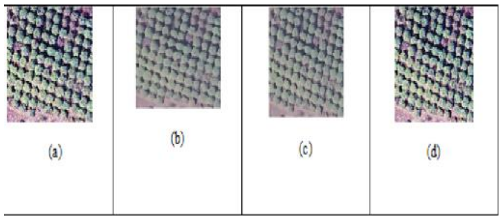

Figure 5 Simulation results of quality enhanced secured data transmission in agricultural area image (a) noisy input (b) Auto Encoder (AE) deep learning-based compression [1] (c) burrows-wheeler transform [2] (d) proposed DGAEL-MMR method

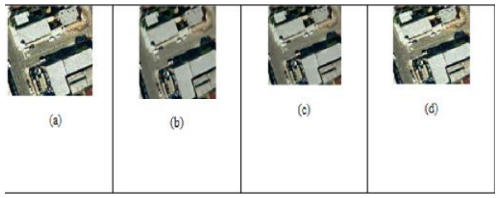

Figure 6 Simulation results of quality enhanced secured data transmission in building area image (a) noisy input (b) Auto Encoder (AE) deep learning-based compression [1] (c) burrows-wheeler transform [2] (d) proposed DGAEL-MMR method

From the above simulation results it is inferred that quality enhancement was said to be performed well using proposed DGAEL-MMR method and hence quality enhanced secured transmission is said to be achieved.

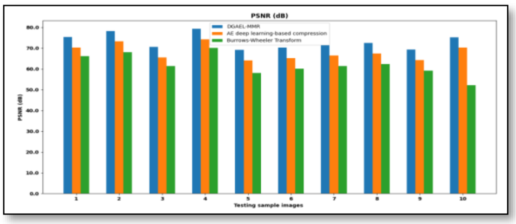

Figure 7 Graphical representation of PSNR

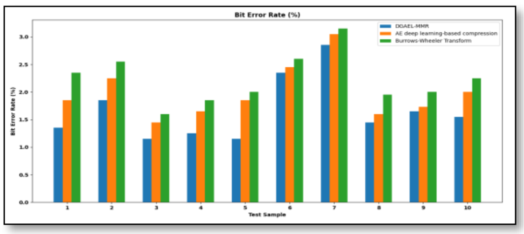

Figure 8 Graphical representation of Bit Error Rate

Figure 7 and figure 8 given above illustrate the pictorial representations of PSNR and BER using the proposed DGAEL-MMR and existing methods [1] and [2]. With 10 compressed images provided as input and 10 iterations being performed two quality enhancement metrics was measured. First, PSNR was found to be higher using DGAEL-MMR upon comparison to [1] and [2]. The reason was by applying the Bernstein–von Mises theorem makes use of compressed satellite image-dependent, locally varying via local mean and standard deviation and then asking thresholds using forward and reverse process with the purpose of adapting regression function to the varying characteristics of the visual data. This in turn reduces the distortion and therefore reducing the MSE considerably. Also by means of Bernstein–von Mises theorem perceptual quality enhancement via abstract data in dispersed manner is designed that ascertains to reverse the dispersion process for generating the satellite image data samples from compressed image. As a result the PSNR is said to be improved using DGAEL-MMR method by 7% compared to [1] and 19% compared to [2]. The BER on the other hand is found to be comparatively lesser using proposed DGAEL-MMR method than [1] and [2]. The reason was due to the application of Bernstein–von MisesMarkovian Kernel Regression Optimization algorithm. By applying this algorithm, for transmission of satellite images, the compressed images were initially subjected to local mean and standard deviation for obtaining finer details. Second, perceptual quality enhancement process was performed by utilizing Bernstein–von function. Finally, median filtered values were subjected to three spatial directions using Kernel Regression function. This in turn improved the bits being transferred after the compression process. As a result the overall BER was found to be improved using DGAEL-MMR method by 19% compared to [1] and 27% compared to [2] respectively.

6 Conclusion

Secured Quality Enhanced Compressed Satellite Image Data transmission is one of the most desirable research areas that may assist by providing lot of information for monitoring natural disasters from small to large regions globally, predict earthquake, analyzed cyclone damage and so on. Past research works underscore satellite image data transmission using different traditional and non-traditional methods, including machine learning, deep learning. In this work, a Deep Gradient Adversarial Extreme Learning and MisesMarkovian Regression quality-enhanced secure image transmission (DGAEL-MMR) is proposed. The individual procedures associated with the organization are secure compressed image data transmission and quality enhancement. First, the sample satellite images are acquired from different samples and provided as input to the Stochastic Gradient Generative Adversarial Network and Extreme Image Compression algorithm. With the extreme learning and stochastic gradient GAN secure image data transmission of satellite images are performed. Next, the compressed images are provided as input to the Bernstein–von MisesMarkovian Kernel Regression Optimization algorithm. Here, quality enhancement in terms of PSNR and BER are said to be ensured using Bernstein–von Mises theorem and Kernel Regression function. The proposed DGAEL-MMR method is experimented in Python high-level, general-purpose programming language using UC Merced Land Use Dataset. The experimentation results validated that the DGAEL-MMR method imparts better results in performance metrics like, data confidentiality, data integrity, PSNR and BER compared to the conventional methods.

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