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Hybrid Framework for Secure Satellite Image Transmission using Adversarial Learning and Mises Regression

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Abstract: - Digital image processing is crucial for reducing file sizes and improving image quality. Image compression reduces the amount of bits looked-for to digitally signify an image, although quality improvement involves making adjustments to the compressed image to restore its original image. With the rapid development of communication networks, it is essential to research efficient and secure transmission of multimedia data. A new method, DGAEL-MMR, is proposed to improve security and quality of picture communication. This method uses two parts: picture compression and quality improvement. The DGAEL-MMR method uses a deep learning model that takes satellite photographs as input of satellite images to ensuring the safety by sustaining privacy and authenticity. Ensure for improve the worth of satellite images compression, a model derived from Bernstein-von Mises Markovian Kernel Regression Optimization is used. Quality improvement criteria like bit error rate (BER) and peak signal to noise ratio (PSNR) are used to assess and compare the model's performance. The DGAEL-MMR technique outperforms traditional approaches in both quality enhancement and security features.

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

I. Introduction

Prior to enhancing the quality of an image, digital cameras compress it. To accomplish loss picture compression, the authors of [1] suggested a technique based on deep learning called Auto Encoder (AE). In this instance, researchers used the structural similarity index metric (SSIM) to assure a high compression rate without sacrificing quality. They achieved this by using an image filter with binarized information and a stacked AE (SAE) for picture compression. Furthermore, a classification model employs a convolutional neural network (CNN) to identify the compression model for every photo class in order to further increase compression rate and picture quality. We did not compare the quality evaluation, bit error rate, or peak signal to noise ratios original and compressed pictures using secure transmission compression, despite improvements in compression rate and picture quality.

Due to the known loss of specific pixel sections during compression, quality augmentation is seen as a conventional method in image compression. Nevertheless, security precautions are required for certain applications to guarantee the image's dependability and legitimacy. Data exposure to different assaults is another worry that arises from the necessity of stringent security measures, such as the control of secret keys through specialized procedures. Although encryption is still the most common method of keeping sensitive data secure using a secret key, it is not without its limitations. To overcome this difficulty without sacrificing the efficiency of either compression or encryption, we presented a technique that uses the Burrows-Wheeler transform simultaneous compression and encryption [2]. We employed a secret-key based compression approach, which is both effective and secure, to accomplish this goal. We failed to prioritize quality improvement, despite the fact that we saw advances in security.

DGAEL-MMR (Deep gradient adversarial extreme learning and mises markovian regression) is a hybrid method that combines the above-mentioned approaches to improve the transmission of satellite images while keeping the quality safe. DGAEL-MMR's contributions include enhancing the quality of satellite image data transmission using the DGAEL-MMR technique. To improve the secrecy and integrity of satellite pictures, here we offer a deep stochastic gradient generative adversarial network, a secure data transfer model for extreme image compression-based. We are using a Bernstein-von Mises Markovian Kernel Regression Optimization-based perceptual quality improvement to increase PSNR and BER, and we verify the results through a large-scale simulation by means of the UCM Dataset.

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The paper is organized as: A two-part staging of relevant studies cutting-edge the area of compressed satellite image data transfer with assured quality enhancement is provided in Section 2. One side of the section describes strategies for improving quality, and the other side concentrates on methods for securely transmitting data. Also included is a synopsis of the knowledge vacuum on techniques for improving quality and secure data transfer. Topic technique and system model are laid forth in Section 3. Section 4 approach secure image transmission for enhancing the quality of image using pseudocode representation is described. Section 5 presents the findings and debate, while Section 6 offers final thoughts.

II. Related Works

This part goes over in detail the different ways that data can be compressed and improved for quality-enhanced safe transfer.

A. Protocols for transmitting data via secure compression of satellite images.

In a number of offline and online real-time applications, image data is crucial. In addition, scientists have found that field imaging systems are very useful for a variety of purposes, including illness diagnosis and anomaly detection using satellite photos. Extensive storage capacity and sophisticated security procedures during transmission are required in line for to the huge and subtle nature of the data of satellite imaging. An attacker might potentially gain sensitive information by attacking the communication channel while it is being sent. A hybrid approach combining wavelet confusion and diffusion was used for the picture compression procedure in [3]. Results for PSNR and MSE both improved as a result of this. Despite deep learning's importance, data collecting, processing, and transmission are common points of vulnerability. Consequently, one of the most important needs is for safe deep-learning inference services.

A general post-quantum approach that combines encryption with plaintext deep learning to guarantee reliable transmission was suggested in [4]. Displayed an additional aggressive compression method that places a premium on fast delivery in [5]. One of the main challenges in data science remains discovery a balance between the two competing goals of data security and feature extraction. To fill this void and lessen the likelihood of sensitive information leaking, [6] proposed a data governance approach that takes into account suitable data management and sharing procedures. The approach successfully achieved a middle ground between being too literal and compromising on data protection. In order to greatly improve the compression ratio, researchers in [7] developed a novel deep learning-based compression technique for medical photos. In order to ensure safe transmission in digital image processing, researchers reviewed deep learning approaches in [8].

A remarkable leap forward in multimedia and communication has been heralded by the ubiquitous monitoring systems in the last several years. In addition, data transfer is made more challenging by the surrounding circumstances and the nature of subterranean projects, which are both caused by the inadequate security techniques that are deployed.

To address the concerns about picture transmission security, the authors of [9] designed a compressive sensing technique based on a gradient Hopfield neural network that can be fine-tuned. Using deep learning networks to emphasize security features, we developed yet another safe cloud-based picture architecture in [10] that focuses on processing medical images. Nevertheless, the design failed to consider the PSNR and BER aspects that are crucial for safe transmission. Using block luminance and deep learning, we were able to close this gap in [11], with an emphasis on performance evaluation parameters.

Multimedia technology has come a long way in the last many years. These days, many individuals choose to share multimedia files using the Internet. Nevertheless, there are a lot of security holes in the Internet, making it a very vulnerable medium. To further ensure the confidentiality and integrity of multimedia files, experts have suggested a number of compression algorithms. Using a deep neural network, the authors of [12] created a logistic map that places an emphasis on quality and security.

Secure picture transmission was achieved by combining ALO (Ant Lion Optimization) with DHT (Diffie-Hellman-based two fish cryptography) in [13]. In addition, using a hybrid system enhanced precision while consuming minimum time and causing low delay. But we left out the transmission error ratio. For this reason, the authors of [14] used an unsupervised variational encoder. Efficient transmission with a minimum error ratio was discovered using this encoder. In [15], it was suggested that deep neural networks and the RSA method could be used in another way to ensure safe communication. Both the material and the speed of the training. Both the training speed and the data confidentiality were greatly improved by implementing RSA on deep neural networks. [16] Using a spindle convolutional auto encoder, we offered a data transfer approach that is both energy efficient and computationally difficult, minimizing reconstruction error.

TABLE 1 A SYNOPSIS OF THE KNOWLEDGE GAPS SURROUNDING METHODS FOR TRANSMITTING DATA SECURELY VIA COMPRESSION OF SATELLITE IMAGES

Reference	Salam Fr et al. (2023)	Qian Chen et al. (2023)	Isaac Shiria et al. (2024)	Mayada Khairy et al. (2022)	Abdulmohsen Almalawi et al. (2024)
Methodology	(AE) deep learning-based compression method	PyHENet	PRIMIS	DLBL	Hybrid cryptographic mechanism
Secure Compression Based Data Transmission	Stacked Auto Encoder	Nil	Deep Sparsifying Transform Learning	Block luminance adopting deep learning	ALO and DHT
Quality Enhancement	Nil	Combines cryptography with plaintext deep learning libraries	Nil	Nil	Nil
Parameter Improved	Reconstruction accuracy, SSIM	Accuracy	Security	Compression ratio, PSNR, and SSIM	High accuracy, low time consumption, and delay

B. ENHANCEMENTS IN THE QUALITY OF SECURE DATA TRANSPRT METHOD

Compressing satellite photos for use in earth observation is still a tedious and time-consuming operation since the quality is lost in the process. Additionally, in terms of quality enhancement, large-scale photographs might potentially offer far better resolution, geographical coverage, and temporal frequency.

[17] Researchers have explored various approaches to improve the quality of resolution in satellite image processing. [18] [19] Two deep learning approaches were used, including a hybrid fitness function and ensemble, forest, and boosting methods. Though, the bit error rate of transmission remained not addressed. [20] Self-FuseNet was developed for extremely low-resolution satellite photos, using deep neural networks for super resolution enhancement.

TABLE 2 SYNOPSIS OF KNOWLEDGE GAPS ABOUT APPROACHES FOR IMPROVING DATA TRANSMISSION QUALITY

Reference	Baritha Begum et al. (2023)	Lavanya Sharma et al. (2020)	Pau Gallés et al. (2024)	Xiaowen Zhang et al. (2023)	Trong-An Bui et al. (2024)
Methodology	Burrows-Wheeler Transform	Improved technique	IQUAFLOW	Improved particle swarm optimization algorithm	Edge-computing-enabled inference model
Secure Compression Based Data Transmission	Burrows-Wheeler Transform	Nil	Nil	Nil	Nil
Quality Enhancement	Ensured security	Entropy and histogram analysis	Deep learning task as a proxy	Contrast enhancement	Deep learning approach
Parameter Improved	Quality aspects were not focused	MSE	SSIM and PSNR	Minimal running time	PSNR and SSIM

Drawbacks	BER was not analyzed	BER was not analyzed	BER was not focused	BER was not analyzed	BER was not included

III. APPROACH AND CONCEPTUAL FRAMEWORK OF THE PROBLEM

A. Problem Methodology

This session described about compression rate achieved while preserving quality in satellite GAEL-MMR. The initial step involves establishing a framework for a secure data transfer method for satellite images utilizing Deep Stochastic Gradient Generative Adversarial Networks and Extreme Image Compression. This paper details the application of Bernstein-von Mises Markovian Kernel Regression Optimization for enhancing the quality of compressed images.

1) The Deep Stochastic Gradient Generative Adversarial Network and Extreme Image Compression for Secure Data Representation

A stacked auto encoder (SAE) was utilized for image compression, accompanied by an image filter employing binarized data. A convolutional neural network (CNN) classification model was employed to identify the compression model for each image class. The Stack Auto Encoder (AE) serves as a method for deep learning-based compression, facilitating the compression and decompression of images without the need for active information processing. A lightweight binary filter was utilized to enhance the quality of the input image. The image classifier, utilizing CNN, identified the appropriate pre-trained Stack Auto Encoder for compression and decompression according to the content analyzed. This strategy effectively trains a large single SAE model capable of compressing and decompressing any image, independent of its content. However, the method lacks provisions for protecting sensitive information or the authenticity of compressed pictures, which are major concerns for security professionals. To address these gaps, the DGAEL-MMR technique, based on Mises-Markovian Regression and deep gradient adversarial learning, is proposed for secure transmission of satellite pictures.

The primary goal of our suggested DGAEL-MMR.

To present a framework of hybrid secure image compression and enhanced quality image transmission for satellite imagery.

- To develop a deep stochastic gradient generative adversarial network and an extreme image compression-based secure data transfer system to improve the confidentiality and integrity of satellite land image.
- Bernstein-von Mises Markovian Kernel Regression Optimization is a model designed to enhance quality by using Bernstein-von Mises and Kernel Regression to improve PSNR and BER.
- To examine the influence of many performance indicators, including PSNR, BER, secrecy, and integrity, on the efficacy of the approach, yielding insights for the optimization of training and deep learning algorithms in data transmission.

B. CONSTRUCTION OF SYSTRM

The DGAEL-MMR algorithm combines secure and quality improved compression for satellite pictures, aiming for secure data transmission and quality enhancement. The model uses the UCM dataset as input pictures for strenuous study, with a stochastic gradient generative adversarial network in the hidden layer. The decoder verifies data validity using a randomly generated key for safe transmission. The model for enhancing perceptual quality is based on Bernstein-von Mises Markovian Kernel Regression Optimization. The model uses statistical functions like mean and standard deviation on compressed satellite photos, and forward and reverse processes utilize Bernstein-von for perceptual quality operation. The kernel regression function is practical in the direction of optimize and improve the quality of photos for safe data transfer.

IV. PROPOSED METHODOLOGY

The DGAEL-MMR quality-enhanced secure image transmission is described in depth in this section. Our first step is to lay out the framework for a secure data transfer method for satellite photos that uses DSGGAN and EIC. We describe in detail how Bernstein-von Mises Markovian Kernel Regression Optimization may be used to improve the quality of compressed pictures.

A. *DSGGAN and EIC* (the deep stochastic gradient generative adversarial network and extreme image compression) -Based Secure Data Transmission

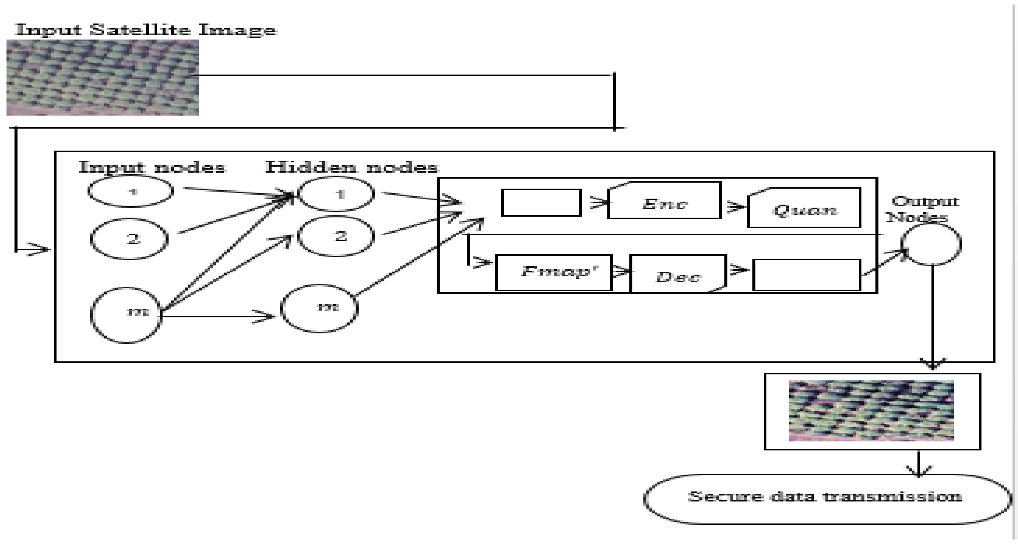


FIG. 1CRITICAL PATH SKETCH FOR SAFE DATA TRANSFER USING DSGGAN AND EXTREME IMAGE COMPRESSION

The transmission of satellite images over densely populated regions is crucial for examining crime scenes and other forms of criminal investigation. However, security issues may arise from the transmission of satellite images via public networks. To address this, a new model for safe data transmission is presented, combining a conditional Generative Adversarial Network with an Extreme Image Compression-derived fine-tuned bit rate. The DSGGAN is the foundation of this model, which uses the input as “SI" for compression and consists of two separate procedures: DSGGAN and fine-tuned weight augmented extreme image compression.

The model aims to develop a safe data transfer of satellite photos using example photos retrieved from the UCM Land use dataset. Encoders then quantizes in the DSGGAN compress the input sample picture before applying it to the hidden layer, or hidden nodes within it. The discriminator creates a random key to confirm the validity of the data transmission. The procedure is started by an alternate set of generators, and the output for one hidden layer is represented mathematically.

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

The equation (1) above ‘w_i’ represents the fine-tuned weight output of the ‘i’ hidden node, which is the model input image. Below is mathematical representation the hidden node.

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

The network regulates the flow of data (i.e., satellite images received from transmission) by applying the fine-tuned weight mentioned above. Additionally, the formula for the hidden layer output mapping of EL is given below.

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

Based on the formulation (3) mentioned earlier, the output matrix 'H' for the hidden layer is provided below.

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

The diagram illustrates a safe data transfer process for satellite photos using example photos from the UC Merced Land Use Dataset. The process involves encoders and quantizers compressing the input image before applying it to the hidden layer. A random key is created by the discriminator to confirm the validity of the decoder. Data transmission is initiated by an alternate set of generators. The output of hidden layer is mapped using stochastic gradient generative adversarial networks, consisting of an encoder, decoder, and quantizer. A unique key is generated for each generator, ensuring the recipient's identity.

As seen here, the encoder takes the optimized, quality-enhanced picture and turns it into a feature map. Then, the hidden layer of extreme learning compresses the values by quantizing them

$$‘CI = Fmap' = Quan(Enc(SI))’ \quad (5)$$

Conversely, the decoder restores the picture using the reconstruction map, seen below.

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

Next, the entropy ‘H(〖Fmap〗^')’ evaluates the average number of bits needed for encoding‘〖Fmap〗^'’'. The stochastic gradient function delineates the balance between reconstruction quality and bit-rate efficiency, as illustrated below.

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

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

The degree of homogeneity between 'SI' and 'SI' is quantified by the loss function in equation (7). The optimization of the bit rate, which is accomplished by fine-tuning the weight in respect to the entropy 'H(Fmap')', is also denoted by the phrase 'W_i (n)'. This optimization pertains to the flow of data or satellite photographs. To provide secure communication between the generator and receiver through a discriminator, the hidden layer of EL is fine-tuned using the Stochastic Gradient function. The pseudo code form illustrates secure data transfer using DSGGAN with Extreme Image Compression.

The aforementioned technique is designed to improve the security and privacy of transmitted satellite photos between users, most especially between the generator and the user. In order to accomplish this, it uses a hidden layer to learn the input sample picture to its extreme. To manage the data flow that the discriminator compresses, this layer does weight fine-tuning. Data confidentiality is guaranteed in this way. Our next step is to use adversarial networks that use stochastic gradient generating techniques to map the output of the hidden layer. The discriminator then verifies the generator's legitimacy by producing a random key to use with the stochastic gradient GAN. After authentication is successful, the generator compresses data and, at the same time, is checked by other sets of generators.

We outlined steps for secure data transmission using Extreme Learning (EL) and Stochastic Gradient GAN (SG-GAN) look well-structured. Here’s a concise summary of the process:

Initialization: Set parameters (n) and (\eta = 0.5).

Begin Process:

For each dataset (DS):

Extreme Learning:

Derive the output function for a single hidden layer containing (L) hidden nodes.

Fine-tune the weights.

Map the hidden layer output for a single sample image.

Map the hidden layer output for (n) sample images.

Stochastic Gradient model GAN:

Generate a key randomly (RK) for generation of each.

Compress the data.

Reconstruct the map.

Evaluate the rate-distortion trade-off.

Obtain the key (RK') from the receiver.

Verify if (RK = RK'):

If true, the receiver is genuine, and secure data transmission occurs.

If incorrect, continue with a different set of generator and receiver.

End the process.

ALGORITHM 1 ENCRYPTED DATA TRANSFER USING A DEEP STOCHASTIC GRADIENT GENERATIVE ADVERSARIAL NETWORK AND HIGHLY COMPRESSED IMAGES

C. Analysis of perceptual quality improvement using Bernstein-von Mises Markovian Kernel Regression Optimization.

When it comes to processing and transmitting encrypted satellite images, one of the first things to worry about is quality improvement, whose main objective is to make the compressed image seem better. The uses of digital picture devices are vast and varied, including fields as diverse as environmental evaluation, landscape analysis, weather forecasting, and many more. The quality of the compressed picture is compromised or degraded due to insufficient compression ratio during data transfer and compression operations for satellite images. We contend that quality enhancement and compression go hand in hand since a greater compression ratio reduces picture quality by packing more data into a smaller space.

Unfortunately, there are a lot of internal and external factors that might make it impractical to improve the compressed image quality while transmission. Improvement of compressed image quality during transmission is thus crucial in many contexts. Perceptual quality, especially when retrieved from big pictures, is still an open question, even though several materials and approaches have been suggested just before improve the feature of compressed images during transmission.

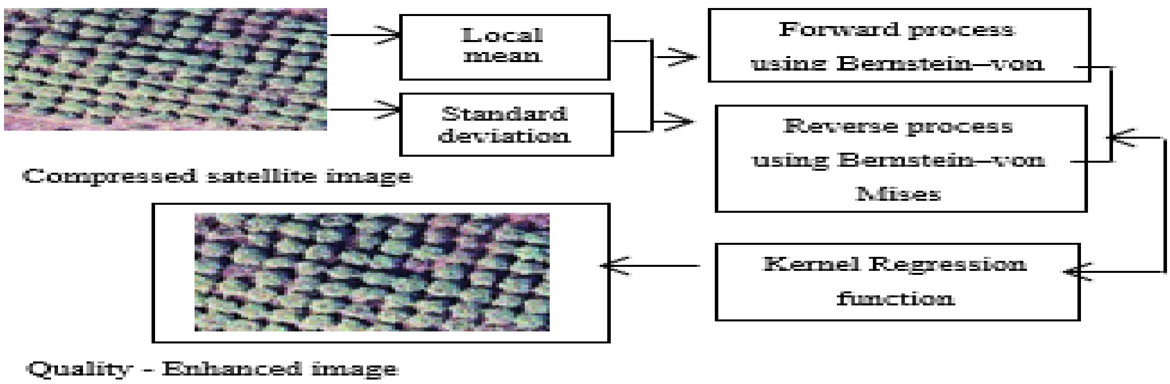


FIG.2 VISUAL QUALITY IMPROVEMENT METHODOLOGY BASED ON BERNSTEIN-VON MISES MARKOVIAN KERNEL REGRESSION OPTIMIZATION: A BLOCK DIAGRAM

Optimization-based methods have been proposed to improve satellite photo transmission quality. One such method is the GMKR (Gaussian Markovian Kernel Regression) optimization, which uses a Bernstein-von Mises theorem and Gaussian Markovian Kernel Regression to enhance perceptual quality. This approach increases performance and computational complexity by dynamically adjusting principal picture and perceptual statistics, thereby enhancing perception quality.

The Bernstein-von Mises and Kernel Regression functions are used to enhance the quality of compressed satellite pictures. The first step involves abstracting data in a scattered manner and then reversing the dispersion process to produce data samples for the design satellite image, thereby improving the perceptual quality. The quality of visual data is enhanced through perceptual quality enhancement, which uses compressed satellite images with local mean and standard deviation. Forward and reverse processing mask thresholds, constructing mean and standard deviation outcomes. The Bernstein-von Mises function constructs forward and reverse processes, while the Kernel Regression tool improves satellite picture data quality. Expressions are generated for local mean and standard deviation.

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

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

The forward process of improving perceptual quality involves a Gaussian dispersion approach, which calculates the mean and standard deviation of compressed image values. The Perceptual Quality Enhancement model uses a Gaussian Markovian transform to learn the distribution of training data. The forward process adds a Gaussian Markovian function to obtain a clean image, CI_0, using Bernstein-von.

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

Equation (11) represents the perceptual factor for each compressed image and the Gaussian Markovian chain of compressed images. As a representation of the intermediate results, the quality enhanced image 'QEI' stores the resulting values. Using Bernstein-von methods, the following is the formulation of the posterior distribution, also known as the reverse process, to maximize the picture PSNR during quality improvement:

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

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

The increased quality of the satellite picture is restored by calculating a sequence of unimportant perceptual components applying the Kernel Regression function to equations (12) and (13).

The noiseless pixel value can be calculated using the Kernel Regression function, based on the pixel coordinates in the satellite image. Another way of putting it is that the assessment is dependent on the relative variance of the pixels. Afterwards, in order to have the enhanced picture quality In order to acquire the median filtered values, the 'X' is passed through a Kernel Regression function in three spatial directions with a smoothing parameter 'δ' that is set to decrease as the volume of the training sample picture rises up to the 'k-th' nearest training instance. The mathematical expression of this is given below.

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

To improve the quality of data transmission, the optimization formula is mathematically represented using the Kernel Regression function, as described below.

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

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

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

The Bernstein-von function is used to optimize the quality of satellite images by applying the ‘mat' function to the diagonal matrix, pixel near position, and perceptualized samples. This process, combined with the Kernel Regression function, improves image quality during transmission. The compressed pictures undergo local means and standard deviation to enhance finer details, thereby improving the quality of satellite photos and enhancing the perceptual quality.

We steps for optimizing and enhancing the quality of compressed satellite images are well-structured. Here’s a concise summary:

Initialization: Set parameters (n) and coordinates (p, q).

Begin Process:

For each dataset (DS) with compressed images (CI):
Evaluate Local Statistics:
Calculate the local mean and standard deviation for the satellite image of size (n \times n).
Perceptual Quality Enhancement:
Apply the Bernstein–von method for perceptual quality enhancement.
Median Filtering:
Obtain median filtered values in three spatial directions.
Kernel Regression:
Use Kernel Regression to enhance the image quality.
Return the optimized quality-enhanced image (opt).
End the process.

ALGORITHM 2 OPTIMIZED QUALITY ENHANCEMENT USING BERNSTEIN-VON MISES MARKOVIAN KERNEL REGRESSION

To get optimal, high-quality output with a low bit error rate, the median filtered data are next sent via a Kernel Regression function over three spatial dimensions.

V. RESULT AND DISCUSSION

We assess the efficacy of the proposed DGAEL-MMR procedure, which stands for DGAEL with MMR quality enhancement for safe picture transmission. Furthermore, we take a close look at two popular approaches: the Burrows-Wheeler Transform [2] and the Auto Encoder (AE) deep learning-based compression [1]. Python, a versatile high-level programming language, is employed to implement these concepts. Downloaded from http://weegee.vision.ucmerced.edu/datasets/landuse.html, the UC Merced land use dataset is used in this investigation. An Intel Core i5-6200U at 4.30 GHz, 4 GB of DDR4 RAM, and 4 cores powers the whole experiment.

A. Data Description

The study uses the UCM land use dataset to develop a safe and improved compressed satellite image transfer method. The dataset contains 21 images from various subjects, including agricultural, airplane, beach, construction, chaparral, and baseball field. The images are sourced from the USGS National Map collection of urban area imagery. The proposed DGAEL-MMR procedure is assessed for secure picture transmission. The study also examines two popular approaches: Burrows-Wheeler Transform and Auto Encoder deep learning-based compression. Python is used to implement these methods. The system is run on a 4.gigabyte DDR4 RAM system and an Intel Core i5-6200U CPU with four cores.

B. Evaluating the Performance of Secure Transmission of Satellite Image

According to equation (18), the data integrity of a model for secure picture data transfer is crucial for ensuring data confidentiality. The data confidence rate is calculated by dividing the amount of model pictures received by the authorized receiver by the sample data used in the simulation. The data integrity is assessed by determining the proportion of unaltered sample photos out of the total input images, ensuring the security of the data transfer.

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

According to equation (18), the level of data confidentiality 'DC' is calculated by considering the sample data used in the simulation 'Samples_i' and the sample instances received by the intended receiver 'Samples_IR'. The metric is expressed as a percentage. Subsequently, the data integrity of the provided satellite pictures is assessed to verify and analyze the assurance of secure image data transfer. Data integrity is quantified as the proportion of sample photos that remain unaltered by any human users out of the total sample images given as input. The data integrity is rigorously defined mathematically as follows.

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

Equation (19) quantifies the data integrity 'DI' by evaluating the sample pictures used for simulation 'Samples_i' and the number of sample compressed images that have not been modified by any malicious users 'Samples_NA'.

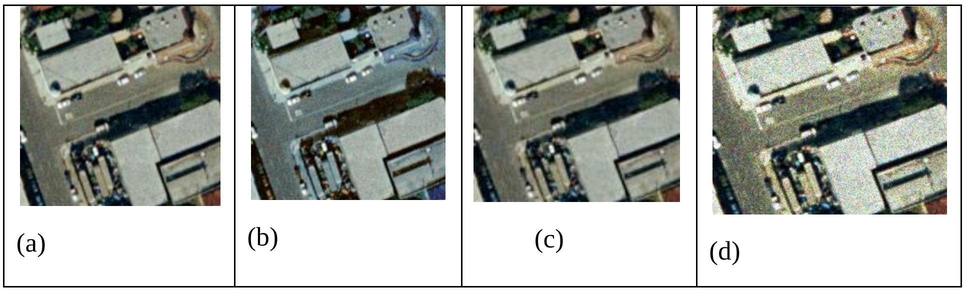


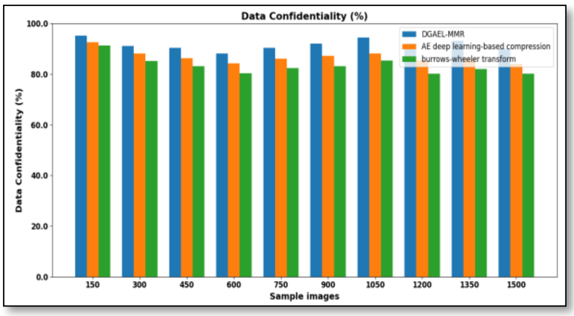
FIG.3 THE RESULTS OF SIMULATION INVOLVING THE SECURE TRANSFER OF DATA IN A BUILDING AREA USING COMPRESSION ARE SHOWN IN FIG.4. (A) INPUT NOISE, AND (B) COMPRESSION USING A DEEP LEARNING ALGORITHM CALLED AUTO ENCODER (AE) [1] THE BURROWS-WHEELER CHANGE [2] (D) THE SUGGESTED TECHNOLOGY, DGAEL-MMR

The proposed DGAEL-MMR method effectively performs compression, ensuring secure transmission. Data confidentiality and integrity are ensured, as shown in Table 3, comparing it to existing methods.

TABLE 3 COMPARING DGAEL-MMR, AE DEEP LEARNING-BASED COMPRESSION [1], AND THE BURROWS-WHEELER TRANSFORM [2] IN TERMS OF DATA INTEGRITY AND SECRECY IS SHOWN.

Sample images	**Data confidentiality (%)**			**Data integrity (%)**		
	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

The tabulation results show that data confidentiality and integrity do not decrease with sample size, despite variations in image size. Simulation results using 150 sample images and DGAEL-MMR showed overall data confidentiality of 95.33%, 92.66%, and 91.33%, respectively. The proposed DGAEL-MMR method surpassed previous methods, ensuring data integrity of 97.33%, 94.66%, and 93.33%.



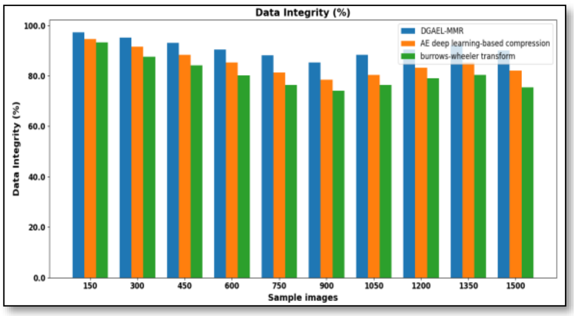


FIG.1 DATA CONFIDENTIALITY: A VISUAL DEPICTION

FIG.2 VISUAL DEPICTION OF PRECISION IN DATA

The study validates secure satellite image transmission using graphical representations of data confidentiality and integrity. The DGAEL algorithm are used to compress input satellite images, ensuring only intended users receive them. The Deep Extreme Learning Machine is used in the input layer to compress the images, verifying their authenticity using a discriminator with a random key. The proposed DGAEL-MMR method improves data confidentiality by 6% and data integrity by 7% and 13%, respectively, for a dataset of 21 land use images.

C. Study of the PSNR and Bit Error Rate performance of secure data transmission with improved quality.

This section utilizes PSNR and BER to validate and evaluate the results of quality enhancement. The Peak Signal to Noise Ratio (PSNR) is characterized as the ratio between the maximum possible power of a signal and the power of the accompanying noise.

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

Following from equation (20), we get the mean square error, abbreviated as "MSE," which stands a measure of the average of the squares of the mistakes.

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

PSNR (Positive Signal Ratio) and BER (Bit Error Rate) are measured to ensure secure, quality-enhanced data transmission. PSNR is measured based on actual image transmission and The Bit Error Rate (BER) is the number of bit errors per unit time divided by the total number of bits transmitted.

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

Figures 7 and 8 provide simulation results for quality improved secured data transfer employing algorithms such as DGAEL-MMR, burrows-wheeler transform, deep learning-based compression, and noisy pictures. The Auto Encoder was used to determine bit error rate.

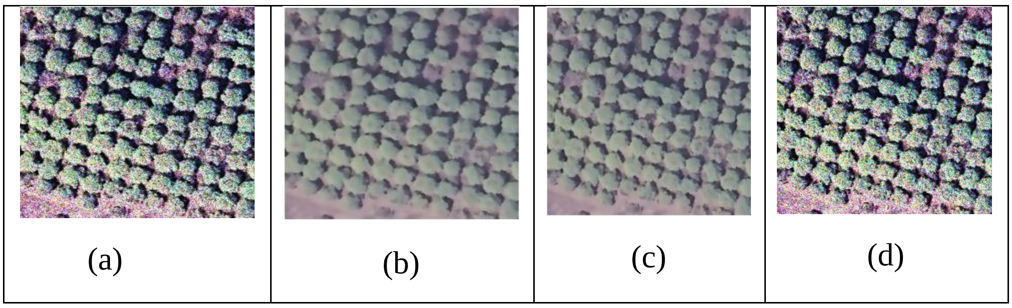


FIG.3 SIMULATION RESULTS OF QUALITY ENHANCED SECURE DATA TRANSMISSION IN AN AGRICULTURAL AREA IMAGE ILLUSTRATES THE SIMULATION RESULTS OF QUALITY ENHANCED SECURED DATA TRANSMISSION IN AN AGRICULTURAL AREA IMAGE. (C) BURROWS-WHEELER TRANSFORM [2] (D) PROPOSED DGAEL-MMR METHOD

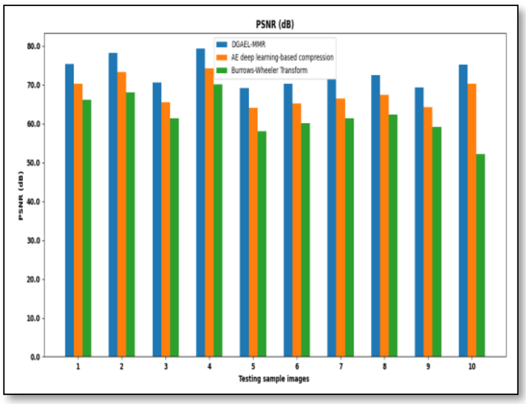
FIG.7 THE OUTCOMES OF A SIMULATION STUDY ON QUALITY-ENHANCED SECURE DATA TRANSMISSION IN A BUILDING AREA PICTURE USING (A) AUTO ENCODER BASED DEEP LEARNING (AE) AND (B) A NOISY INPUT [1]. THE BURROWS-WHEELER CHANGE [2] (D) WE SUGGEST THE DGAEL-MMR TECHNIQUE.

The simulation results demonstrate that the suggested DGAEL-MMR method outperforms the competition thanks to its better performance and higher transmission quality and security. In order to get the findings, the values from the proposed DGAEL-MMR method and the AE deep learning-based compression were substituted into equations (20, 21), and (22). Ten representative pictures and two measures of performance, PSNR and Bit Error Rate, were used to evaluate the outcomes. The findings show that the sizes of the pictures used for testing have an effect on the PSNR and bit error rate outcomes. The proposed DGAEL-MMR demonstrates superior PSNR and reduced BER, indicating a more effective quality improvement, resulting in reconstructed images of superior quality.

TABLE 4 THE PSNR AND BER VALUES OBTAINED USING THE BURROWS-WHEELER TRANSFORM, AE DEEP LEARNING-BASED COMPRESSION, AND THE RECOMMENDED DGAEL-MMR TECHNIQUE ARE PRESENTED.

Testing sample images	**DGAEL-MMR**		**AE compression based deep learning**		**burrows-wheeler transform**	
	PSNR (dB)	Bit Error rate (%)	PSNR (dB)	Bit Error rate (%)	PSNR (dB)	Bit Error rate (%)
1	75.35	1.35	70.33	1.85	66.23	2.35
2	78.25	1.85	73.23	2.25	68.13	2.55
3	70.55	1.15	65.53	1.45	61.43	1.6
4	79.35	1.25	74.30	1.65	70.20	1.85
5	69.15	1.15	64.10	1.85	58.00	2
6	70.25	2.35	65.20	2.45	60.10	2.6
7	71.45	2.85	66.42	3.05	61.32	3.15
8	72.45	1.45	67.43	1.6	62.33	1.95
9	69.35	1.65	64.32	1.73	59.22	2
10	75.25	1.55	70.21	2	52.11	2.25

As an example, the input agricultural testing image produced a PSNR of 75.35 dB by the suggested DGAEL-MMR, as opposed to 70.33 dB and 66.23 dB for the previous two studies [1] and [2], respectively. Three different approaches produced BER values: 1.35 percent, 1.85 percent, and 2.35 percent. This proves that the suggested DGAEL-MMR improves upon the quality enhancements made in [1] and [2].



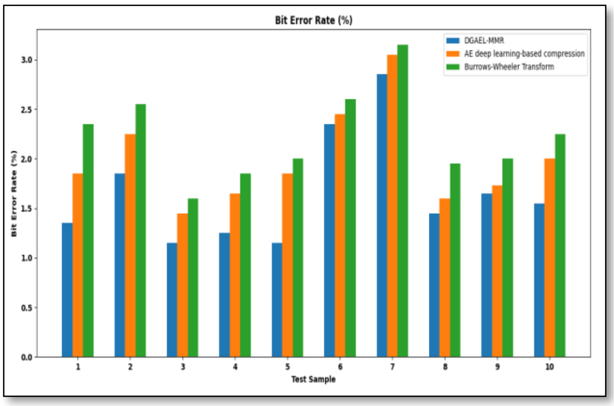


FIG.4 PRESENTATION OF PSNR DATA GRAPHICALLY

FIG.5 A VISUAL DISPLAY OF BIT ERROR RATE

The suggested DGAEL-MMR and current approaches [1] and [2] are depicted graphically in Figures 7 and 8, respectively, to show PSNR and BER. After 10 rounds and 10 compressed photos as input, we assessed two quality enhancement measures. The DGAEL-MMR technique outperformed both [1] and [2] in terms of PSNR, to begin with. The Bernstein-von Mises theorem, which uses compressed satellite pictures that differ close by according to the standard deviation and mean, is responsible for this. Next, it adjusts the regression function to the visual data's unique properties by setting thresholds using forward and reverse operations.

Thus, distortion decreases, lowering mean square error. The Bernstein-von Mises theorem also proposes a dispersed way to increasing perceptual quality utilizing abstract data by inverting the dispersion process and generating data samples from compressed satellite imagery. The DGAEL-MMR method increases PSNR by 7% and 19% over [1] and [2]. The DGAEL-MMR method reduces BER significantly compared to [1] and [2]. It began with Bernstein-von Mises Markovian Kernel Regression Optimization. Our satellite picture transmission method initially applied the local mean and standard deviation to compressed images for enhanced information. 2nd, use Bernstein-von function to increase visual quality. The median-filtered data were analyzed using three-dimensional kernel regression. This increased post-compression data transport. The DGAEL-MMR method improved overall BER by 19% and 27% over [1] and [2].

VI. CONCLUSION

Here to exploring the potential of secure, quality-enhanced compressed satellite image data transfer to improve our ability to track earthquakes, evaluate cyclone damage, predict earthquakes, and monitor natural disasters on a global scale. This study discusses an approach called DGAEL-MMR, which combines Deep Gradient Adversarial Extreme Learning with Mises Markovian Regression to enhance the quality of secure image transmission. This paper implements an adversarial network and extreme picture compression approach using stochastic gradient generating methods after collecting satellite images from various locations. The Bernstein-von Mises Markovian Kernel Regression Optimization algorithm is then used to improve the quality of PSNR and BER in the compressed images. The DGAEL-MMR strategy was tested using the UCM dataset and high-level, general-purpose computer language Python. The findings demonstrated that the DGAEL-MMR technique is superior to traditional approaches in terms of performance measures such as data confidentiality, data integrity, PSNR, and BER.

VII. FUNDING STATEMENT

No specific funding was received by the authors for this study.

VIII. CONFLICTS OF INTERST

The authors report no conflicts of interest related to the current study.

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