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GANNET OPTIMIZATION ALGORITHM BASED VECTOR QUANTIZATION FOR CODEBOOK CONSTRUCTION WITH ENCRYPTION SCHEME FOR INDUSTRIAL EMBEDDED PLATFORMS

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Abstract

In industrial environment, image data from surveillance, quality examination, and machine vision methods need effectual compression and safe handling to meet real-time operational needs. Vector quantization (VQ) tackles this requirement by decreasing higher-dimensional image data into a representative code vector, allowing major compression without compromising vital visual data. The efficiency of VQ mainly based upon codebook construction, where a carefully intended set of codewords seizes the numerical properties of industrial images. Optimization models are employed in this procedure to minimalize distortion, enhance the quality of reconstruction, and adjust dynamically to fluctuating imaging conditions. By incorporating enhanced codebook construction with VQ, industrial models can attain effective fast transmission, image storage, and decreased computational load, while also supporting encryption systems for secure communication—creating this technique essential for scalable, intelligent, and secure image processing in industrial environment. This article presents a new Gannet Optimization Algorithm based Vector Quantization for Codebook Compression with Encryption Scheme (GOAVQ-CCES) technique for industrial platforms. The presented GOAVQ-CCES approach applies the LBG with the GOA for optimal construction of VQ. The LBG technique is widely used for designing the local optima codebook to compress the images. Since the design of codebooks are represented as an optimization process and can be eliminated using GOA. At the same time, the codebook generated from the LBG-VQ undergo optimization for accomplishing an optimum codebook. For encryption process, certificate-based signcryption with a proxy re-encryption (CBSRE) is utilized to encrypt the codebook and achieves security. To validate the performance of the GOAVQ-CCES approach, a detailed simulation analysis is conducted. The comparison analysis stated the supremacy of the GOAVQ-CCES approach over other methods.

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1. Introduction

Vector Quantization (VQ) is an information compression technique. The core concept of VQ-compressed images is to split images into non-overlapping pixel blocks and give every pixel block as a vectors [1]. This method, namely the Linde–Buzo–Gray (LBG) approach or other enhanced approach, is utilized for training images into a codebook. The image's pixel blocks are further charted to the nearest codeword in the codebook, and the indexes of those codewords are saved as an index table [2]. Currently, information hiding in the compression field of VQ-compressed images has been an effective area of study [3]. The majority of the studies used methods for hiding information within the index tables, while a few current studies discovered an approach to hide information within the codebooks [4]. Generally, VQ may be categorised into memory VQ and memory-less VQ. Vector quantization is a process that shatters the information to be encoded into minor vectors or blocks that are successively encoded vector by vector [5]. The concept for identifying a set, or ' codebook', of potential vectors that are representative of the data to be encoded. VQ comprises three phases: Encoding, Decoding, and Codebook Designing. The VQ encoder matches every source vector with the nearest matching vector from the codebook, thus quantizing it. The real encoding is then easily a process of successively listing the individual codewords, whereas it is regarded as very closely matching the vectors creating the initial information [6]. The encoder and decoder share the same codebook, and decoding is an insignificant substance of piecing together the vectors of which individuality have been particularized.

The major part in VQ is for designing a good codebook of illustrative vectors, characteristic of the information to be sent. The highly computationally difficult role in the design of a VQ-driven coding/decoding system is the codebook creation [7]. Effective VQ of images based on constructing appropriate codebooks: The standard of the last image is crucially dependent on the standard of the codebook, and codebook construction methods could be extremely slow. Recently, machine learning (ML) methods have been among the most important and strong technical developments. It enables analysing a huge amount of information and automatically captures intricate and ambiguous patterns within the information [8]. ML methods, particularly those that depend on NN, have been demonstrated to be extremely effective and thriving in a broad range of real-life applications. With this huge ability involved in these environments, they can expect that ML could be utilized for improving efficacy also in a broad range of upcoming applications involving VQ for codebook creation [9].

This manuscript presents the Gannet Optimization Algorithm based Vector Quantization for Codebook Compression with Encryption Scheme (GOAVQ-CCES) system for industrial platforms. The proposed GOAVQ-CCES model employs the LBG with the GOA for optimum VQ construction. The LBG method is broadly utilized for designing the local optima codebook to compress the images. Since the design of codebooks are characterized as an optimization process, and can be eliminated by GOA. At the same time, the codebook generated from the LBG-VQ undergoes optimization to accomplish an optimal codebook. For the encryption

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process, certificate-based signcryption with a proxy re-encryption (CBSRE) is employed to encrypt the codebook and achieve security. The comparison analysis stated that the supremacy of the GOAVQ-CCES model with existing approaches.

2. Related Works

Gao et al. [10] presented an adaptable modem that depends on a VQ long short-term memory autoencoder (LSTM-AE), intended for implementing demodulation and modulation of signals from the second to the thirty-second in a trivial method. Next, the Adam optimizer was utilized to train and test on an easy information expanded by enhancing AWGN noise only and making alterations. Lin et al. [11] introduced an information hiding system for VQ codebooks. With the method, a sender XORs among the pixel data in codebook and relates it to threshold for controlling embedded information. When receiving the phase of codebook and rearranged index table, the receiver could obtain the information and rebuild the VQ-compressed image employing the reverse method. Sihwail and Ibrahim [12] proposed a new image encryption approach known as the smart codebook that integrates an intelligent codebook method with the RSA (Rivest–Shamir–Adleman) technique. This approach is intended to be dynamic as it decides the highly efficient codebooks in encrypting every image to improve its ambiguity. The presented approach separates an image into various sections depending on the picture dimensions, and several random codebooks are created for every section. Furthermore, images undergo different processing phases as they are changed into cipher images, involving encryption, segmentation, and noise.

Kumar and Srinivasan [13] introduced an artificial hummingbird optimization method that integrates LBG-aided codebook creation and encryption (AHBO-LBGCCE) to be utilized in an IIoT environment. This approach employed the LBG method in combination with the AHBO approach for constructing the VQ. Moreover, the Blowfish technique is exploited for performing the encryption process so that safety can be reached. Yang et al. [14] suggested an innovative uplink interaction compression approach for FL, termed FedMPQ, that depends on a multi-shared codebook product, this http URL, for using modernizations from the preceding round for creating adequately strong codebooks. Secure aggregation is then attained across a trusted third party (TTP) or a trusted execution environment (TEE).

Gao et al. [15] examined the susceptibilities of RDHEI that depend on BPCM encryption and presented a cryptanalysis approach that depends on the VQ threat. This approach doesn't need the assistance of plaintext image contrast to adopt the reversible property among the encrypted cover image and innovative cover image. Lin et al. [16] presented an undamaged compression system for the VQ index table. This method is intended for recompressing VQ compression techniques and restoring them to the VQ compression transferor without losing. It is significant that the approach particularly aims at texture images. Through utilizing the spatial symmetry characteristic in those images, the method creates greater frequency signs across multiple analyses, which simplifies the utilization of adaptable Huffman coding for effective compression.

3. Proposed Methodology

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In this article, we have been presented a novel GOAVQ-CCES method for industrial platforms. The presented GOAVQ-CCES model uses the LBG with the GOA for optimal construction of VQ. To achieve this, the GOAVQ-CCES system comprises different steps described in this section.

3.1. Preliminaries of VQ

VQ is one of the lossy data compression models in a block of code. The invention of the codebook named the vital process of VQ [17]. Suppose the dimension of the new image $Y = \{y_{ij}\}$ is MxM pixel splits diverse blocks with dimensions of nxn pixels. In other terms, there is $N_b = [\frac{N}{n}] \times [\frac{N}{n}]$ block that denotes a set of input vectors $= (x_i, i = 1,2, \dots, N_b)$. Deliberate L as nxn. An input vector $\chi_i, \chi_i \in \Re^L$ while $\Re^L$ is L-dimensional Euclidean space. The model of VQ allocates the input vector by connecting the codeword, and that substitutes the relevant input vector for achieving the goal. The optimizer of C with respect to MSE stated to lessen the distortion function D. Usually, the low rate of D is the high value of C.

$$D(C) = \frac{1}{N_b} \sum_{j=1}^{N_c} \sum_{i=1}^{N_b} \mu_{ij} \cdot \|x_i - c_j\|^2 \tag{1}$$

subjected to the succeeding limitations:

$$\sum_{j=1}^{N_c} \mu_{ij} = 1, \forall i \in \{1,2, \dots, N_b\} \tag{2}$$

$$\mu_{ij} = \begin{cases} 1 \; if \; \chi_i \; is \; jth \; cluster; \\ 0 \; otherwise \end{cases} \tag{3}$$

similarly

$$L_k \leq c_{jk} \leq U_k, k = 1,2, \dots, L \tag{4}$$

While $\|x - c\|$ denotes the Euclidean distance amid the vector χ and codeword c, U_k signifies the maximal of k_{th} component in every vector of input and L_k implies the minimal of k_{th} component in every training vector.

Dual conditions for optimal VQ.

1. The partition $R_j, j = 1, \dots, N_c$ is reach

$$R_j \supset \{x \in \chi : \; d(x, c_j) < d(x, c_k), \qquad \forall k \neq j\}. \tag{5}$$

2. The codeword c_j offers the centroid of R_j:

$$c_j = \frac{1}{N_j} \sum_{i=1}^{N_j} x_i \, , x_i \in R_j, \tag{6}$$

While N_j denotes the entire number of vector that belongs to R_j.

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3.2. LBG Algorithm

The LBG method is used to design the local optima codebook for image compression. LBG model is an overview of Lloyd's model for a multi-dimensional space [18]. It matches the clustering model that begins with a primary outcome, which is iteratively enhanced to fulfill the nearest neighbor condition and centroid. LBG initiates with a codebook, which frequently contains random vectors gained by the trained set, for instance $Z = \{\vec{z}, q = 1,2, \dots, Q\}$, with $\vec{z}_q = \{z_{q1}, z_{q2}, \dots, z_{qK}\}$, that is upgraded at every iteration, depend on the computation of the centroids of every Voronoi area.

$$y_{ij} = \frac{1}{Q_i}\sum_{\vec{z}\in S_j} z_{qj} \quad (7)$$

Whereas z_{qj} signifies the j_{th} element $\vec{z}_q$ and Q_i denotes the counts of training vectors in the region S_i.

It monitors every iteration and lessens monotonically. This criterion has been accomplished, end the procedure, while the percentual distortion variation diminishes the existing iteration regarding to the preceding one.

$$\frac{D_{t-1}-D_i}{D_t} \leq \epsilon \quad (8)$$

While ϵ matches the distortion threshold and D_i equivalent to distortion assessment in t_{th} iteration. LBG is summarize in the succeeding steps:

- Step1 (initialized): set Y_0 as primary codebook, set $t = 0$, and distortion is $D_{-1} = \infty$.
- Step2 (partitioning): Assume Y_t be codebook in t_{th} iteration, assign every training vector $\vec{z}_q$ in the Voronoi area.
- Step3 (distortion calculation): To evaluate the overall distortion.
- Step4 (stop criterion): If the stop criterion has been satisfied, the model stop and return Y_t depicting the final codebook; otherwise, continue.

Step5 (update code vectors): To assess the novel centroids of every Voronoi region. Assume $t = t + 1$ and returns to Step2.

3.3. Steps Involved In Based Codebook Construction

In addition, the design of the codebooks are signified as an optimization process and can be removed utilizing GOA. GOA is a metaheuristic optimizer model motivated by the natural behaviors [19]. Primarily, it inspires the natural predating features of gannets. It simulates the principle of genetic inheritance and the existence of the fittest and expands a population toward near- or optimum outcomes. In nature, the optimizer contains dual phases: exploitation and exploration. Now, the gannets were presumed that the initial population, and it is arbitrarily initializing with boundary rates.

$$n_{p,q} = d_1 \times \left(upB_q - lwB_q\right) + lwB \quad (9)$$

Now, the location of p_{th} hunting agent of $\mathrm{q_{th}}$ size is identified by $n_{p,q}$. Subsequently, the lower and upper limits are lwB and upB, correspondingly. Eventually, the random value lies among

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zero and one specified in d_1. Whereas, the term YT denotes the matrix of memory. In iteration, the location of gannets has been modified that is reflected by the memory matrix.

Exploration: Gannets hunt for prey on the surface of water. Naturally, 2 kinds of dive, such as U-shape and V-shape.

$$u = 2 * cos(2 * \pi * rd_2) * n \quad (10)$$

$$v = 2 * X(2 * \pi * rd_3) * n \quad (11)$$

Here, $n = 1 - \frac{nc}{nm}$ (12)

In Eq. (12), nm and nc explain the maximal number of iterations and present iteration. Then, rd_2 and rd_3 denotes random values lie among zero and one.

$$G_j(n+1) = \begin{cases} G_j(n) + a1 + a2, p \geq 0.5 \\ G_j(n) + b1 + b2, p < 0.5 \end{cases} \quad (13)$$

Now, $a2 = U * \left(G_j(n) - G_d(n)\right)$, and $b2 = V * \left(G_j(n) - G_a(n)\right)$ (14)

$$U = (2 * rd_4 - 1) * u, V = (2 * rd_5 - 1) * v \quad (15)$$

Now, $G_a(n)$ is average position, $G_d(n)$ refers to a random choice of population, $G_j(n)$ denotes existing searching agent, rd_4 and rd_5 refers to random values among zero and one.

$$G_a(n) = \frac{1}{M}\sum_{j=1}^{M} G_j\,(n) \quad (16)$$

Exploitation: Once the search agent rushing into the surface of water, catch the prey needs even more energy. Gannet contains suitable capability to acquire while it has enough energy.

$$G_j(n+1) = \begin{cases} n * \delta * \left(G_j(n) - G_{bt}(n)\right) + G_j(n), & Cp \geq t \\ G_{bt}(n) - \left(G_j(n) - G_{bt}(n)\right) * Q * n, & Cp < t \end{cases} \quad (17)$$

Where the continuous parameter is specified t. Now, Cp is computed based on the succeeding equations.

$$Cp = \frac{1}{P * n2} \quad (18)$$

$$n2 = 1 + \frac{nc}{nm} \quad (19)$$

$$P = \frac{ma * vy^2}{l} \quad (20)$$

$$l = 0.2 + (2 - 0.2) * rd_6 \quad (21)$$

Now, the arbitrary rate comprises the range from zero to one, given in rd_6. Subsequently, vy and ma refer to velocity and mass of the gannet. Likewise, the term δ is calculated to employ Eq. (22).

$$\delta = Cp * \left|G_j(n) - G_{bt}(n)\right| \quad (22)$$

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$$Q = Lvy(D) \tag{23}$$

The input data is divided into a non-overlapping block that undergoes quantization by LBG model. The codebook has employed the LBG approach trained with GOA model to satisfy global convergence. The transformed index and corresponding codewords are set appropriately for the drive to generate a decompressed data size closely corresponding to the input data.

Step1. Parameter initialization: Currently, the codebook intended to employ the LBG model is specified that the main outcome, while residual outcomes are determined in arbitrary model. The achieved solution denotes the codebook of N_c codewords.

Step2. Selecting the existing optimal solution: the process of every fitness solution and choose the greater fitness place as the greater solution.

Step3. To create a novel solution: the position is improved by employing the prey location. When the arbitrarily created number (K) is greater than $\sim a$, subsequently interchange the bad position with newly recognized place and preserve a better placed unchanged.

Step4. Ranking the solution in fitness function (FF) application and choosing an optimum solution.

Step5. End Condition: succeeding the step2 and step3, still gaining the termination criteria. Fig. 1 represents the flowchart of the GOA model.

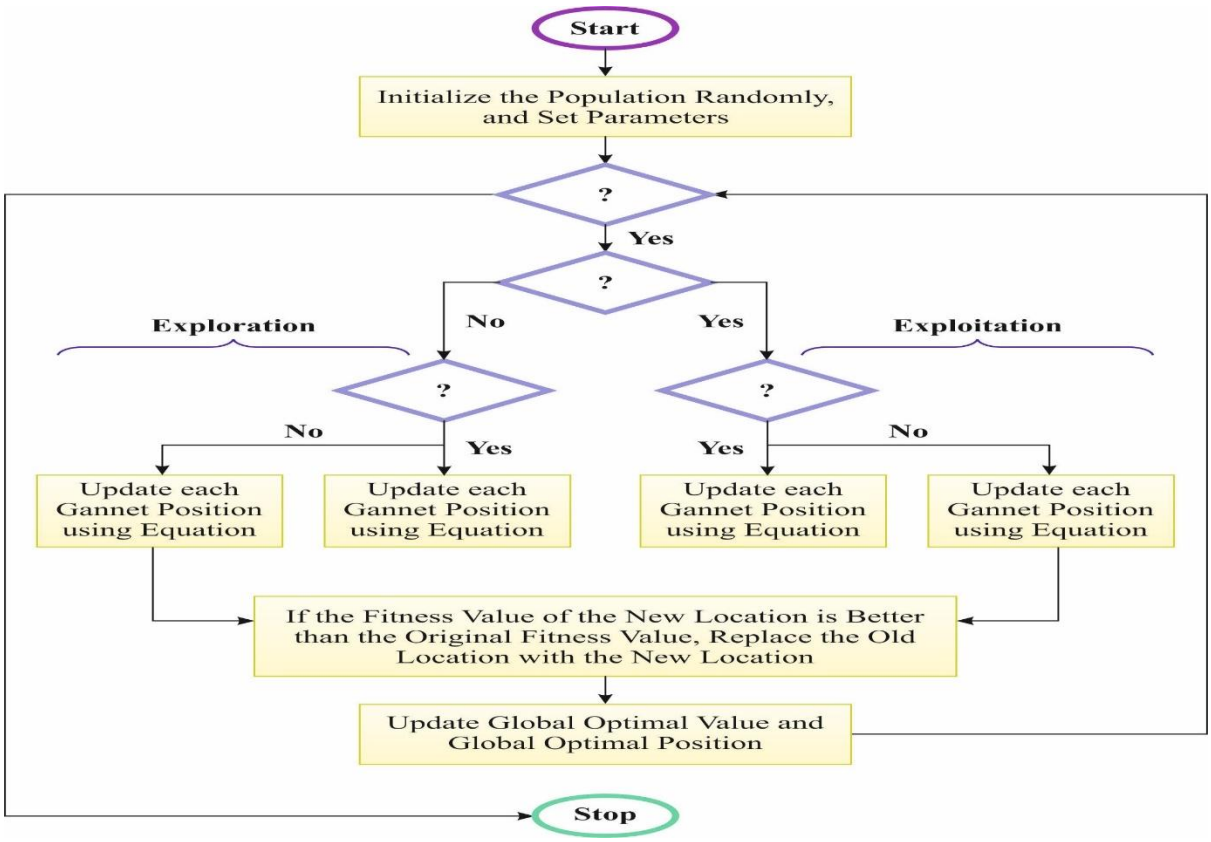

Fig. 1. Flowchart of GOA model

3.4. Encryption Scheme

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For encryption process, CBSRE is used to encrypt the codebook and achieves security. This part comprises the structure of the CBSRE model and its sub-stages like Setup, Certi_cations, Key Generation, Unsigncryption, Re-encryption Key Generation, Signcryption, Re-encryption, and Decryption, correspondingly [20]. The novel CBSRE method is actually the extended version and includes 9 steps.

Setup

This stage was performed by Certifiers Authority (CsA), it acquires the security parameter π as input. Likewise, it creates a general set of parameters which are given below.

- Choose a genus dual hyperelliptic curve ($\mathcal{HC}$) by an 80-bit key and dimension of parameter.
- Choose 3 single-way collision resistance function, which means, $\hbar_0, \hbar_1, \hbar_2, \hbar_3, \hbar_4$ and these functions are SHA512.
- Choose $\mathscr{b}\epsilon Z_n$ and calculate $\mathcal{R} = \mathscr{b}.\mathcal{D}$ as a main PBK, here $n = 2^{80}$
- Calculate $\mho = (\mathcal{HC}, \hbar_0, \hbar_1, \hbar_2, \hbar_3, \hbar_4, n = 20^{80}, Z_n, \mathcal{R})$.

Key-Generation

A consumer with ID_υ will generate his public key (PBK) and private key (PRK): it chooses the PRK $\alpha_\upsilon \epsilon Z_n$ and set $\hbar_\upsilon = \alpha_\upsilon$, subsequently evaluate a fractional PBK $\mathcal{PP}\beta_\upsilon = \alpha_\upsilon.\mathcal{D}$. It acquires an input π and $\mho$.

Certifications

Specified $\mho, \mathcal{R}, ID_\upsilon$, and $\mathcal{PP}\beta_\upsilon, C_sA$ arbitrarily pick $\delta_\upsilon \epsilon Z_n$ and calculate a complete PBK with ID_υ as: $\mathcal{FP}\beta_\upsilon = (\mathcal{Puk}_{\upsilon I}, \mathcal{Puk}_{\upsilon II}) = \mathcal{PP}\beta_\upsilon, \delta_\upsilon.\mathcal{D})$ and permit $\mathcal{C}er_\upsilon = \delta_\upsilon + \mathscr{b}\hbar_0(ID_\upsilon, \mathcal{FP}\beta_\upsilon)$.

Signcyption

To give an sender identity ID_s, input $\mho$, sender PRK $\mathcal{P}\hbar_s$, receiver's ID_r, and massage (m), correspondingly. This model generates the text of signcrypted cipher $\psi = (\mathcal{C}_s, \mathcal{G}, \mathcal{Z})$ by succeeding calculations.

- Choose $\hbar \epsilon Z_n$ and calculate $\mathcal{W} = \hbar.\mathcal{D}$
- It choose $\eta \epsilon \{0,1\}^\gamma$
- Calculate $\dagger = \hbar_1(\eta, ID_S, m)$
- Calculate $\Upsilon = \dagger.\mathcal{D}$
- Calculate $\mathcal{Q}_s = \mathcal{Puk}_{sI} + \mathcal{Puk}_{sII} + \hbar_0(ID_S, \mathcal{FP}\beta_s).\mathcal{R}$.
- Create a Ciphertext as $\mathcal{C} = (\eta, ID_S, m) \oplus \hbar_2(\dagger.\mathcal{Q}_s)$
- Calculate $\mathcal{G} = \hbar_3(\mathcal{W}, \Upsilon, \mathcal{C})$
- Calculate $\mathcal{Z} = \dagger - \mathcal{G}.\mathcal{P}\hbar_s$
- The last one has been evaluated as; $\psi = (\mathcal{C}, \Upsilon, \mathcal{W}, \mathcal{Z})$

Re-Encryption Key Derivation

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To give a receiver's ID_r, input $\mho$, sender identity ID_s, sender certificate $\mathcal{C}er_s$, and $\mathcal{P}k_s$, correspondingly. It evaluate $\mathcal{S} = h_4\big(ID_s, ID_r, \mathcal{P}k_s(\mathcal{P}uk_{sI} + \mathcal{P}uk_{sII} + h_0(ID_S, \mathcal{F}P\beta_s).\mathcal{R})\big)$ and re-encryption key as $\mathcal{RK}_{s\mapsto r} = \frac{\mathcal{P}k_s + \mathcal{C}er_s}{\mathcal{S}}$. It was simple to assume $\mathcal{RK}_{s\mapsto r} = \frac{\mathcal{P}k_s + \mathcal{C}er_s}{h_4(ID_s, ID_r, (\mathcal{P}k_r + \mathcal{C}er_r)}$.

Re-Encryption

To provide input $\mho, \psi = (\mathcal{C}, \Upsilon, \mathcal{W},)$ and $\mathcal{RK}_{s\mapsto r}$, the CS executes the succeeding steps.

- It verifies if $\Upsilon = \mathcal{Z}.\mathcal{D} + \mathcal{G}.\mathcal{P}\mathcal{P}\beta_s$ holds, the set $\mathcal{C}^{/} = \mathcal{C}$.
- Calculate $\Upsilon^{/} = \mathcal{RK}_{s\mapsto r}\Upsilon$
- Set $\phi = \left(\mathcal{C}^{/}, \Upsilon^{/}, \mathcal{Z}, \mathcal{G}\right)$ as a 2nd level cipher-text.

Unsigncryption

To provide input $\mho$, $\mathcal{C}er_r$, ID_s, ID_r, $\mathcal{P}uk_{sI}$, $\mathcal{P}k_r, \phi = (\mathcal{C}^{/}, \Upsilon^{/}, \mathcal{Z}, \mathcal{G})$, the receiver achieves the succeeding steps.

- It initially verifies if $\Upsilon = \Upsilon = \mathcal{Z}.\mathcal{D} + \mathcal{G}.\mathcal{P}\mathcal{P}\beta_s$
- Calculate $\mathcal{S}^{/} = h_4(ID_r, ID_s(\mathcal{P}k_s + \mathcal{C}er_r)\mathcal{P}uk_{sI})$.

Afterward decrypts $(\eta, ID_s, FN_s, m)^{/} = \mathcal{C}^{/} \oplus h_2(\mathcal{S}^{/}\Upsilon^{/})$. Fig. 2 portrays the process of CBSRE approach.

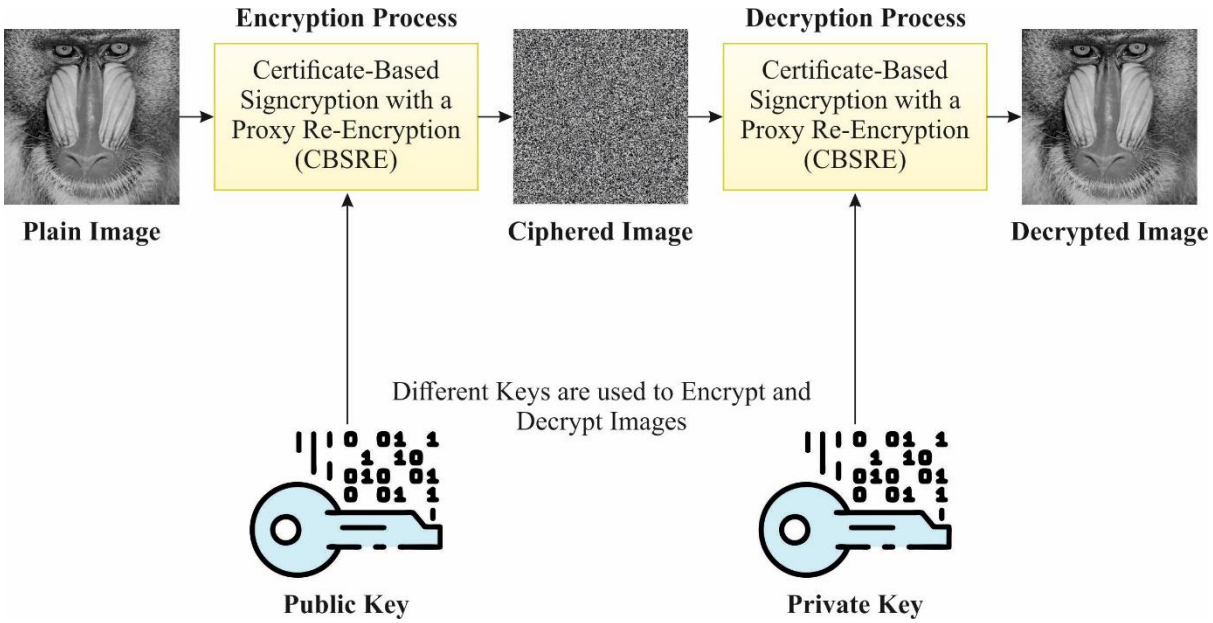

Fig. 2. Process of CBSRE approach

4. Experimental Setup

The performance analysis of the GOAVQ-CCES methodology is examined below. Fig. 3 shows the sample images.

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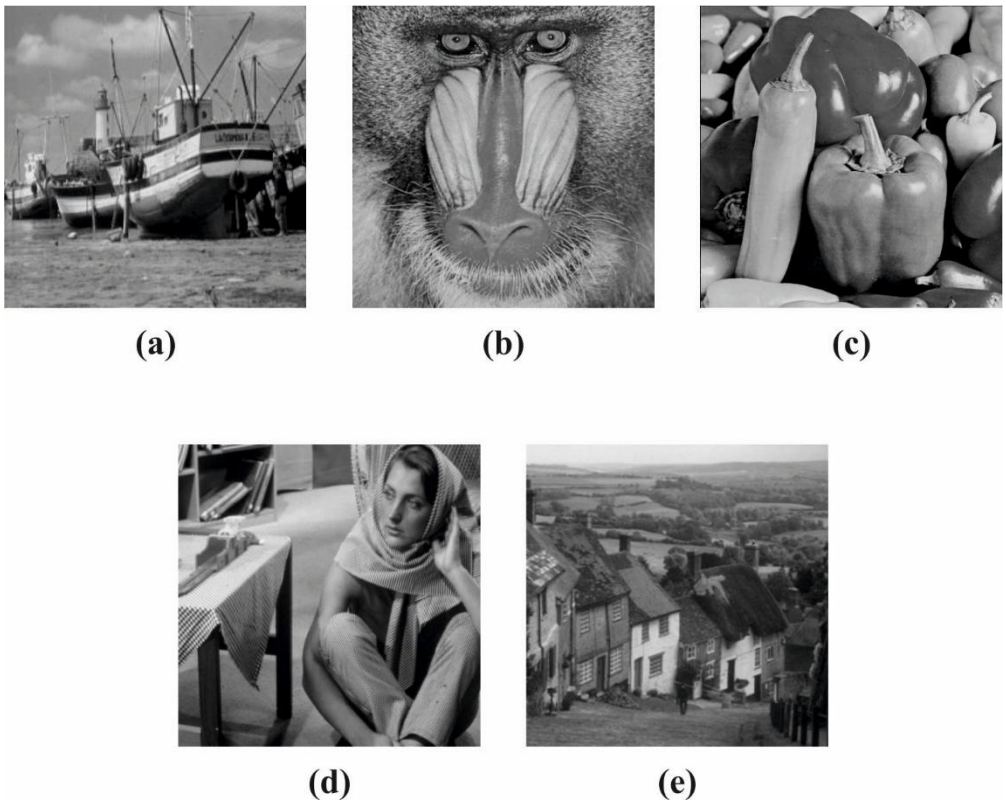

Fig. 3. Sample images (a) Boat, (b) Baboon, (c) Peppers, (d) Barb, (e) Goldhill

Table 1 and Fig. 4 represent the PSNR outcome of the GOAVQ-CCES model with diverse bit rate (BR) levels methods. The outcomes implied that the proposed GOAVQ-CCES has reached higher PSNR values at every BR. For instance, under Image 1, with BR of 0.188, the GOAVQ-CCES system has achieved a greater PSNR of 34.92dB. In contrast, the SHO-VQES, Hybrid LZMA, and CSA-LBG approaches have obtained decreased PSNR values of 30.15dB, 27.04dB, and 26.03dB, correspondingly. Besides, under Image 3, with a BR of 0.250, the GOAVQ-CCES algorithm has gained a maximal PSNR of 35.80dB. In contrast, the SHO-VQES, Hybrid LZMA, and CSA-LBG approaches have obtained decreased PSNR values of 31.17dB, 28.04dB, and 26.05dB, correspondingly. Moreover, under Image 5, with BR of 0.625, the GOAVQ-CCES has reached a maximal PSNR of 41.58dB. In contrast, the SHO-VQES, Hybrid LZMA, and CSA-LBG models have achieved decreased PSNR values of 36.86dB, 33.03dB, and 32.03dB, correspondingly.

Table 1 PSNR outcome of GOAVQ-CCES model with diverse bit rate levels

PSNR (dB)								
No. of Images	**Methods**	**Bit Rate**						
		0.188	0.250	0.313	0.375	0.438	0.500	0.563	0.625

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Image-1 (BOAT)	GOAVQ-CCES	34.92	36.45	37.93	38.73	40.26	40.79	43.17	43.83
	SHO-VQES	30.15	31.71	33.32	34.05	35.66	36.01	38.50	39.11
	Hybrid LZMA	27.04	28.03	30.04	32.03	32.03	34.02	36.05	36.04
	CSA-LBG	26.03	27.04	28.02	30.04	31.04	32.02	34.05	35.04
Image-2 (BABOON)	GOAVQ-CCES	32.34	33.59	34.26	35.41	37.69	37.85	40.25	41.58
	SHO-VQES	27.82	28.86	29.76	30.91	32.91	33.11	35.58	36.99
	Hybrid LZMA	24.04	26.03	27.03	29.03	30.03	30.02	32.03	34.02
	CSA-LBG	23.04	24.04	26.03	28.03	29.04	29.03	31.03	33.02
Image-3 (PEPPERS)	GOAVQ-CCES	34.00	35.80	36.97	37.97	38.65	39.63	40.07	41.12
	SHO-VQES	29.32	31.17	32.21	33.34	34.06	35.07	35.47	36.42
	Hybrid LZMA	26.02	28.04	28.05	30.04	30.04	31.04	32.02	34.02
	CSA-LBG	25.03	26.05	27.03	29.05	30.04	30.02	31.03	33.04
Image-4 (BARB)	GOAVQ-CCES	34.56	36.31	38.11	38.51	40.17	41.29	42.49	43.68
	SHO-VQES	30.01	31.61	33.33	34.01	35.50	36.57	37.94	38.93
	Hybrid LZMA	27.03	28.03	30.04	31.04	32.04	34.02	35.04	36.03
	CSA-LBG	26.04	27.05	28.05	30.05	32.03	32.05	34.02	35.02
Image-5 (GOLDHILL)	GOAVQ-CCES	33.99	34.90	35.70	37.61	37.61	38.81	39.37	41.58
	SHO-VQES	29.32	30.20	30.91	33.10	33.11	34.18	34.73	36.86
	Hybrid LZMA	25.04	25.03	26.03	27.03	29.04	31.03	32.05	33.03
	CSA-LBG	23.05	24.03	25.02	26.03	27.03	30.03	31.04	32.03

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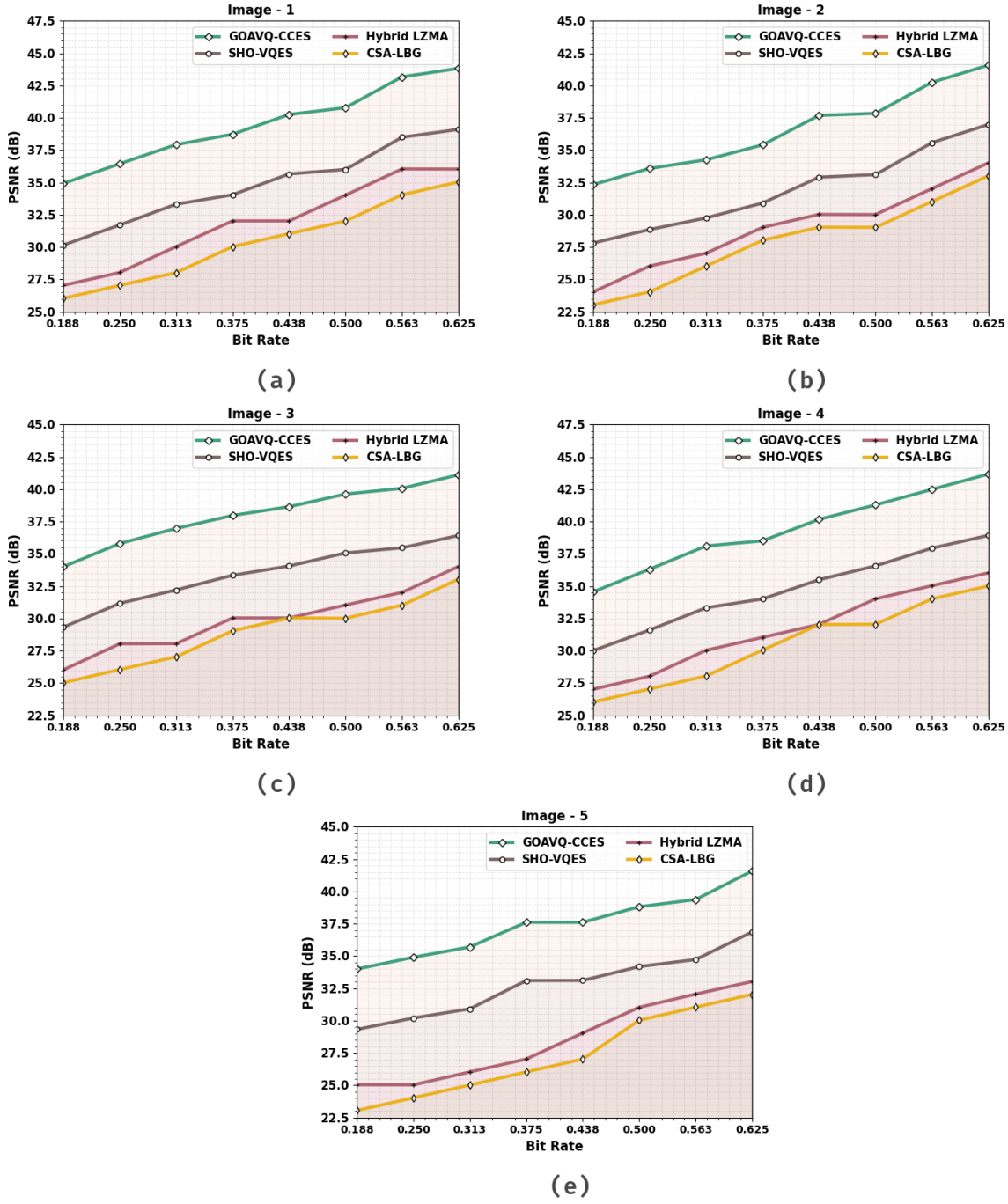

Fig. 4. PSNR outcome of the GOAVQ-CCES model with diverse bit rate levels

Table 2 and Fig. 5 represent the average PSNR outcome of the GOAVQ-CCES with diverse images [21]. Under image 1, the proposed GOAVQ-CCES approach has obtained a higher value of 39.51 dB, while the existing methods, such as SHO-VQES, Hybrid LZMA, and CSA-LBG, have achieved lower values of 34.82 dB, 31.91 dB, and 30.41 dB, respectively. Besides, under image 3, the GOAVQ-CCES model has obtained a superior value of 38.03 dB, while the existing methods, such as SHO-VQES, Hybrid LZMA, and CSA-LBG, have achieved lower values of 33.38 dB, 29.91 dB, and 28.91 dB, respectively. Moreover, under image 5, the proposed GOAVQ-CCES model has obtained a higher value of 37.45 dB, while the existing

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methods, such as SHO-VQES, Hybrid LZMA, and CSA-LBG, have achieved lower values of 32.80 dB, 28.53 dB, and 27.28 dB, respectively.

Table 2 Average PSNR outcome of the GOAVQ-CCES model with diverse images

Average PSNR (dB)					
Methods	**Image1**	**Image2**	**Image3**	**Image4**	**Image5**
GOAVQ-CCES	39.51	36.62	38.03	39.39	37.45
SHO-VQES	34.82	31.99	33.38	34.74	32.80
Hybrid LZMA	31.91	29.03	29.91	31.66	28.53
CSA-LBG	30.41	27.91	28.91	30.54	27.28

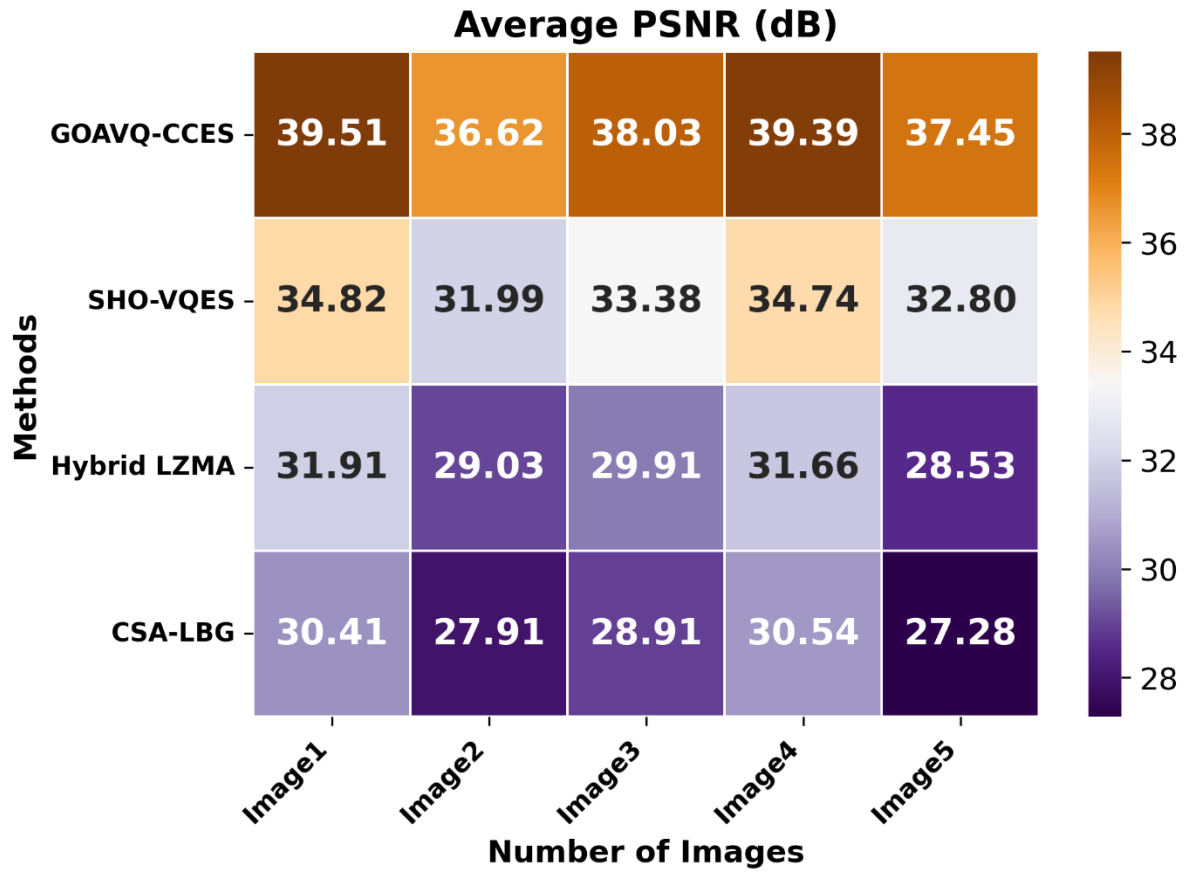

Fig. 5. Average PSNR outcome of GOAVQ-CCES model with diverse images

Table 3 and Fig. 6 represent the average computation time (ACT) of GOAVQ-CCES model with diverse images. Under image 1, the GOAVQ-CCES model has obtained a lower ACT of 126ms, while the existing methods such as SHO-VQES, Hybrid LZMA, and CSA-LBG, have achieved higher ACT of 191ms, 234ms, and 262ms, respectively. Besides, under image 3, the proposed GOAVQ-CCES model has obtained a lower ACT of 155ms, while the existing methods such as SHO-VQES, Hybrid LZMA, and CSA-LBG have achieved greater ACT of 215ms, 252ms, and 250ms, respectively. Also, under image 5, the proposed GOAVQ-CCES

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model has obtained lower ACT of 160ms, while the existing methods such as SHO-VQES, Hybrid LZMA, and CSA-LBG have achieved greater ACT of 220ms, 250ms, and 283ms, respectively.

Table 3 ACT of GOAVQ-CCES model with diverse images

Average Computation Time (ms)					
Methods	**Image 1**	**Image 2**	**Image 3**	**Image 4**	**Image 5**
GOAVQ-CCES	126	128	155	89	160
SHO-VQES	191	192	215	176	220
Hybrid LZMA	234	242	252	245	250
CSA-LBG	262	260	250	265	283

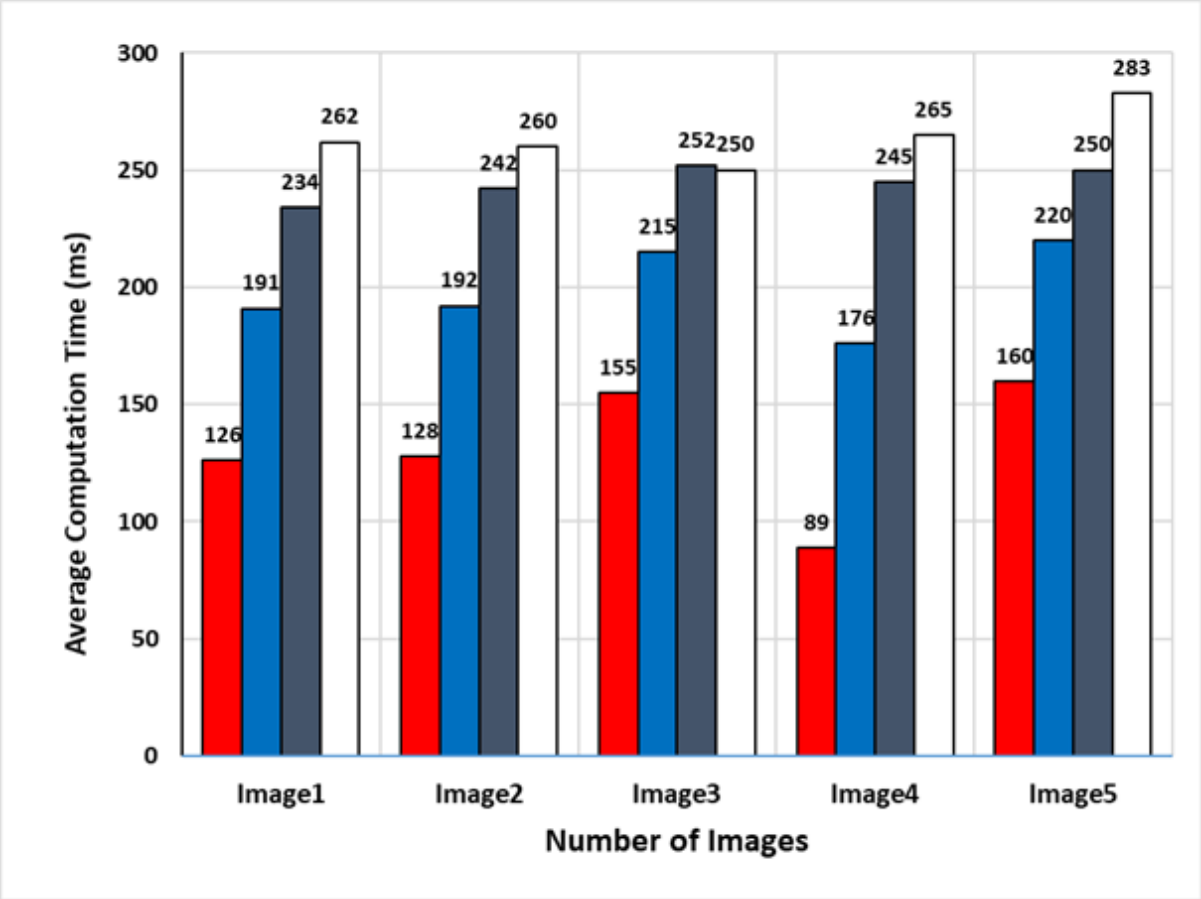

Fig. 6. ACT of the GOAVQ-CCES model with diverse images

5. Conclusion

In this paper, we have presented a novel GOAVQ-CCES method for industrial platforms. The presented GOAVQ-CCES model uses the LBG with the GOA for optimal construction of VQ. The LBG method is broadly to design the local optima codebook for image compression. Since the design of the codebooks is signified as an optimization process and can be removed utilizing

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GOA. Simultaneously, the codebook generated from the LBG-VQ undergoes optimization for achieving an optimal codebook. For the encryption process, CBSRE is deployed to encrypt the codebook and attain security. To authorize the performance of the GOAVQ-CCES approach, a detailed simulation analysis is conducted. The comparison study implied the superiority of the GOAVQ-CCES model over other methodologies.

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