An Energy-Efficient Compression Algorithm of ECG Signals in Remote Healthcare Monitoring Systems

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ABSTRACT Remote Healthcare Monitoring Systems (RHMs) that use ECG signals are very effective tools for the early diagnosis of various heart conditions. However, these systems are still confronted with a problem that reduces their efficiency, such as energy consumption in wearable devices because they are battery-powered and have limited storage. This paper presents a novel algorithm for the compression of ECG signals to reduce energy consumption in RHMs. The proposed algorithm uses discrete Krawtchouk moments as a feature extractor to obtain features from the ECG signal. Then the accelerated Ant Lion Optimizer (AALO) selects the optimum features that achieve the best-reconstructed signal. Our proposed algorithm is extensively validated using two benchmark datasets: MIT-BIH arrhythmia and ECG-ID. The proposed algorithm provides the average values of compression ratio (CR), percent root mean square difference (PRD), signal to noise ratio (SNR), Peak Signal to noise ratio (PSNR), and quality score (QS) are 15.56, 0.69, 44.52, 49.04 and 23.92, respectively. The comparison demonstrates the advantages of the proposed compression algorithm on recent algorithms concerning the mentioned performance metrics. It also tested and compared against other existing algorithms concerning Processing Time, compression speed and computational efficiency. The obtained results show that the proposed algorithm extremely outperforms in terms of (Processing Time = 6.89 s), (compression speed = 4640.19 bps) and (computational efficiency = 2.95). The results also indicate that the proposed compression algorithm reduces energy consumption in a wearable device by decreasing the wake-up time by 3600 ms.

INDEX TERMS Remote healthcare monitoring, signal compression, electrocardiogram (ECG), energy efficiency, krawtchouk moments, Ant Lion Optimizer.

I. INTRODUCTION
According to an American Heart Association report, cardiovascular diseases (CVDs) are one of the leading causes of death worldwide [1]. Medical scientists attributed significant priority to cardiac health studies and focused on scientific advancement in cardiac activity measurement. One such research pathway is the development of traditional cardiovascular diagnostic technology implemented in hospitals and clinics. Monitoring the Electrocardiogram (ECG) is the most extensively used clinical heart check. Due to its straightforward, risk-free, and cheap use has become a valuable test for different cardiac disturbances. Electrocardiogram (ECG) is the electrical activity of the heart [2]. It provides complete information about the heartbeat’s electrical activity simultaneously for a better diagnosis. Each heartbeat in the ECG signal produces various deflections expressed as wave series. The regular heartbeat consists of five waves depicted by five symbols P, Q, R, S, and T, as illustrated in Fig.1. The P wave denotes atrial depolarization stimulation, and a QRS complex is created by atrial repolarization and ventricular depolarization, while The T wave is generated by ventricular repolarization. Continuous health care monitoring enables proactive medical treatment in CVDs. It helps in the
Therefore, the compression technique employed in remote healthcare monitoring systems sensors. The majority of high-performance ECG signal compression methods are inappropriate for wireless biosensors due to their complexity. Therefore, the compression technique employed in remote healthcare systems should be extremely efficient, straightforward, and rapid. In general, effective and efficient compression algorithms should achieve high compression ratios and maintaining the visual quality of the compressed data [8]. This is a significant issue in ECG signal compression since the loss of medical data may result in an incorrect diagnosis. Our work incorporates a range of contributions that can be summarized as follows:

- A highly efficient, rapid, and simple compression technique is well-suited for wireless biosensors in remote monitoring systems. It achieves a high compression ratio, preserving the reconstructed signal’s quality to reduce the energy.
- A modified version of ALO is introduced, which levy flight is applied in Ant Lion Optimizer (ALO) to accelerate it by reducing the number of iterations performed by Accelerated Ant Lion Optimizer (AALO) algorithm in the process of searching for the optimum solutions.
- Experiments demonstrated the proposed algorithm’s superior performance using two different datasets.

The proposed ECG compression technique combines the discrete krawtchouk moments and Accelerated Ant Lion Optimizer (AALO). In the first phase, the discrete krawtchouk moments are used as a feature descriptor of ECG signal. The optimization algorithm (AALO) selects the optimum features that achieve the best-reconstructed signal in the second phase. AALO selects the best feature combination by minimizing the Mean Square Error (MSE) as the objective function.

The remainder of the paper is structured into six sections: section 2 discusses literature review and motivation. Details Krawtchouk moments, Ant Lion Optimizer, and using levy flight in Acceleration ALO algorithm are illustrated in Section 3. We introduce our proposed algorithm in section 4. The numerical experiments, the obtained results, and discussions are shown in section 5. In section 6, we conclude our work in this paper.

II. LITERATURE REVIEW AND MOTIVATION

Due to the importance of ECG in health care monitoring, it was addressed in many research works. In general, there are two main types of ECG data compression techniques: lossless compression techniques and lossy compression techniques. In lossy data compression techniques, the reconstructed signal involves some loss of data. In that way, the lossy compression techniques achieve compression ratios much higher than the lossless compression techniques, but medical regulatory agencies do not accept them. On the contrary, the original signal can be reconstructed from its compressed form in lossless data compression type and cannot reach high compression ratios. However, there is no loss of information in the lossless compression techniques. The reconstructed and original signals are much the same. So these types of compression are more emphasized in ECG signal use [9]. The compression methods for ECG signals are categorized into three
groups: direct compression method, transformational compression methods, and parameters extraction based method. The transformed compression method is often favored among these three categories because these techniques have effective performance in CR and signal restoration.

This method converts the signal from the time domain into other domains and rejects irrelevant coefficients; the key idea is energy redistribution [10]. The transformed based methods include Discrete cosine transform (DCT) [11], discrete Fourier transform (DFT) [12], discrete wavelet transform (DWT) [13], [14]. The previous transforms are used extensively in ECG compression due to their simplicity.

Several ECG compression algorithms were developed based on DWT [10], [15]–[18]. Two dimensional (2D) ECG compression algorithms are modified version of transforms such as DCT [19], 2D-DWT [20], singular value decomposition (SVD) [21]. Using encoding in transformed methods achieves a high CR. Various types of coding are used to compress ECG signals, such as Huffman encoding, run-length encoding (RLE), Lempel ZivWelch (LZW) encoding. Rajoub [22] introduced an ECG data compression algorithm based on efficient encoding. Here, the signal is decomposed into frequency bands using WT, and then efficient coding is applied. Pooyan et al. [23] present an efficient compression method using set partitioning in hierarchical trees (SPIHT) coding. SPIHT compression algorithm is low complexity and achieves high CR with high reconstruction efficiency. Sharifahmadian [24] proposed a novel coding technique to improve compression efficiency called enhanced set partitioning in hierarchical trees (ESPIHT). Other data compression methods are used to compress ECG data, such as; a discrete sin interpolation (DSI) method [25], discrete orthogonal Stockwell transforms [26]. Another work of ECG data compression is applied using the modified embedded zero-tree wavelet (MEZW) is proposed by Tohumoglu and Sezgin [27]. They improved the compression algorithm’s efficiency by experimenting with different wavelet types and threshold values. In the past few years, ECG compression methods have grown significantly in healthcare systems. Kumar et al. [28] introduced a hybrid approach of Singular Value Decomposition (SVD) and Embedded Zero Tree Wavelet (EZTW) techniques. This method achieves a high compression ratio in the telemedicine system. Elgendi et al. [29] introduced Compression ECG data used in E-health applications. They used Decimating by a Factor B/K and TERMA-based QRS detector. Window-based Turning Angle Detection and adaptive tuning of angle threshold introduced by Zhou and Wang [30] to reduce wireless data transmission rate in wearable health care sensor systems. Chandra et al. [31] presented a new algorithm called Cosine Modulated Filter Bank (CMFBs) to Compress ECG data. The ECG signal is encoded by decomposing it into different frequency bands in that algorithm. The threshold for the elimination of the negligible coefficients is implemented. The threshold value is estimated by analyzing any band’s significant energy. Besides, run-length (RLE) encoding is used for compression enhancement. Another work suggested a deep-learning-based spindle convolutional auto-encoder introducing a new algorithm for compressing ECG signals [32]. The spindle convolutional auto-encoder is mainly composed of the convolutional encoder and decoder with functional layers. It has a high CR and ECG compression of outstanding quality. Chagnon and Rebollo-Neira [33] introduced a novel strategy called Mixed Transform in which 1D transformed to 2D conversion of heartbeats, a DWT along with one of the dimensions, and the DCT along the other dimension. Comparative performance analysis of Various Wavelet-Based ECG Compression Methods presented by Chandra et al. [34]. Wavelet transform is used with four coding types: Huffman encoding, Run-Length
encoding (RLE), and Lempel Ziv-Welch (LZW) encoding. Khalid and Boudraa [35] suggested a compression algorithm based on empirical mode decomposition (EMD). For ECG data compression, a combination of EMD and wavelet transform was proposed by Wang et al. [36]. A new ECG compression algorithm was suggested by Jha and Kolekar [37]. This algorithm uses shifting-function-based empirical mode decomposition EMD to get the first intrinsic mode function (IMF), and discrete wavelet transform (DWT) is applied. Then run-length encoding is implemented to obtain a compressed form of ECG signal. Tsai and Tsai [38] developed an ECG compression algorithm to reduce the storage and transmission cost by a multichannel; it employs adaptive linear prediction to account for intra and inter-channel decorrelation. For entropy coding, they additionally employ the adaptive Golomb-Rice codec. Zheng et al. [39] presented a simple and effective approach for decomposing ECG signals using SVD and then the decompressed data to a convolutional neural network (CNN) and supporting vector machine (SVM) for classification. Jha and Kolekar [40] provide a methodological review of multiple ECG signal compression methods. This research investigates the benefits and drawbacks of various ECG data compression strategies. It also offers various ECG compression methodology validation techniques. Although compression techniques have been widely developed, validation of compression methods remains a promising research field for achieving efficient and dependable performance.

In the present era, orthogonal moments have gained importance because they can effectively represent images and signals in many compressions, processing, and pattern recognition applications [41]–[45]. Discrete orthogonal moments are more efficient than continuous orthogonal moments due to the numerical approximation of continuous integral, the normalization of coordinate space, and computation complexity. Coordinate space transformations are not required in discrete orthogonal moments such as Krawtchouk and Tchebichef moments. Moreover, there is no numerical approximation, as the basis in the discrete domain of the space of the image coordinate is orthogonal [46]. Moments based on discrete orthogonal polynomials are commonly used in signal compression. If a discrete orthogonal moment is chosen correctly, the energy in a signal is concentrated on a relatively small percentage of the moment coefficients; these coefficients are then used to generate the reconstructed signal. Hosny et al. [43] propose efficient compression of biomedical signals using Tchebichef moments and Artificial Bee Colony. The Tchebichef moments extract bio-signal features, and the ABC selects the best features that result in the best-reconstructed signal quality. However, there is the main drawback in this algorithm as high time-consuming. This is due to slow convergence and the large number of iterations used in searching for the optimum solution by the ABC algorithm. To overcome this drawback, in this paper, we use Krawtchouk moment as a feature descriptor better than Tchebichef in terms of reconstruction quality and speed Ant lion Optimizer ALO to select the optimum feature achieves optimum reconstructed signal which better than ABC in convergence speed. In addition, we combined ALO with levy flights, which is one type of random walk whose step lengths are not constant but determined by levy distribution. Levy flight makes a large jump in a random walk; this allows the individual to visit new sites that the swarm has not visited, which accelerates the convergence of ALO. Hybrid levy flight with ALO finds optimal features in the lowest number of iterations, reducing time consumption.

### III. PRELIMINARIES AND METHODS

#### A. BLOCK-BASED DISCRETE KRAWTCHOUK MOMENTS

Krawtchouk moments are discrete orthogonal moments obtained from Krawtchouk orthogonal polynomials [47]. The computation of Krawtchouk moments faced numerical fluctuations with higher orders, which led to high reconstruction errors during the compression process. So, we apply a block-based moment computation algorithm to overcome this weakness and retain ideal signal reconstruction. We will use the forward discrete Krawtchouk transform of order \( l \) to extract the features of the signal and the inverse Krawtchouk transform-based to reconstruct the signal.

For a signal with length \( L \), the forward discrete Krawtchouk transform of order \( l \) is formulated as follows:

\[
K_l = \sum_{x=0}^{L-1} k_l(x, p)s(x) \quad l = 0, 1, 2 \ldots L.
\]  

(1)

The inverse Krawtchouk transform-based signal reconstruction is formulated as:

\[
S(x) = \sum_{l=0}^{L} K_l k_l(x, p) \quad x = 0, 1, 2 \ldots L - 1.
\]  

(2)

where \( s(x) \) indicates to the original signal, and \( S(x) \) indicates a reconstructed signal, \( K_l \) set of moment coefficients of the signal \( (x) \), and \( k_l \) show the discrete Krawtchouk polynomials of order \( l \), which are defined in the recurrence relation as follows:

\[
k_0(x, p) = \frac{L!p^x(1-p)^{L-x}}{x!(L-x)!}
\]  

(3)

\[
k_1(x, p) = \frac{(-p\cdot(L-x)+x(1-p))\cdot(L-1)!p^{x-1}(1-p)^{L-x-1}}{x!(L-x)!}
\]  

(4)

\[
k_l(x, p) = (x+\beta_1)\beta_2k_{l-1}(x, p) - \beta_3k_{l-2}(x, p)
\]  

(5)

where

\[
\beta_1 = (1-l-p\cdot(L-2l+2))
\]  

(6)

\[
\beta_2 = \sqrt{\frac{1}{p(1-p)(L-l+1)}}
\]  

(7)

\[
\beta_3 = \sqrt{\frac{(L-l+2)(l-1)}{(L-l+1)}}
\]  

(8)

From Eqs. (3) - (5), Krawtchouk Kernel matrix can be formulated as follows (9), as shown at the bottom of the next page.
depending on the block size \( l \), the kernel size is \((l \times l)\). If \( l = 8 \) and \( p = 0.8 \). The \((8 \times 8)\) Krawtchouk Kernel matrix is \(Kernels_{8 \times 8}\), as shown at the bottom of the page.

In general, the block-based forward Krawtchouk transform is calculated using matrix multiplications as:

\[
D = SK^T
\]

(10)

where \( D \) is moment coefficients, \( S \) is a block of the signal, and \( K \) is the Krawtchouk Kernel matrix.

The block-based inverse Krawtchouk transforms is calculated as:

\[
R = DK
\]

(11)

where \( R \) is the reconstructed signal block.

**B. THE BASIC ALO**

Ant lion algorithm inspired from intelligent behavior of antlion’s larvae, where it digs a pit in the cone using its strong jaw. Antlion hides in a cone, waiting for ants or insects to slip on the sand and fall in. The pit’s edge is sharp, leading to the fall of the prey easily. When prey falls in a pit, an antlion slides it into the bottom of the pit. Finally, antlion amends the trap to the next hunt. Whenever the antlion is hungrier, it has been observed the trap is bigger, and it has a higher chance of catching ant [48].

1) A MATHEMATICAL FORMULA FOR THE BASIC ALO

Ant and antlion are main elements over search space; ant moves to search food, and antlion waits to hunt. Firstly, model the position of ant in search space in the following matrix:

\[
H_{\text{ANT}} = \begin{bmatrix}
H_{1,1} & H_{1,2} & \cdots & H_{1,m} \\
\vdots & \vdots & \ddots & \vdots \\
H_{n,1} & H_{n,2} & \cdots & H_{n,m}
\end{bmatrix}
\]

(12)

where \( H_{\text{ANT}} \) is the position matrix for ants over search space, \( H_{i,j} \) is the \( i \)th ant in \( j \)th dimension (variable), \( n \) is the number of ants, and \( m \) is the number of dimensions (variable) in space. The fitness value for ants can be expressed as:

\[
f(H_{\text{ANT}}) = \begin{bmatrix} f(H_{1,1}, H_{1,2}, \cdots, H_{1,m}) \\ \vdots \\ f(H_{n,1}, H_{n,2}, \cdots, H_{n,m}) \end{bmatrix}
\]

(13)

where \( f(H_{\text{ANT}}) \) is the vector for the fitness value for all ants and \( f \) is the objective function.

Besides ant, antlion takes position over search space similar to the ant.

\[
H_{\text{ANTLION}} = \begin{bmatrix} HL_{1,1} & HL_{1,2} & \cdots & HL_{1,m} \\
\vdots & \vdots & \ddots & \vdots \\
HL_{n,1} & HL_{n,2} & \cdots & HL_{n,m}
\end{bmatrix}
\]

(14)

where \( H_{\text{ANTLION}} \) is the position matrix of each antlion is over search space, \( HL_{i,j} \) indicates the position of \( i \)th antlion in \( j \)th dimension (variable). The fitness value of all antlions can be expressed as:

\[
f(H_{\text{ANTLION}}) = \begin{bmatrix} f(HL_{1,1}, HL_{1,2}, \cdots, HL_{1,m}) \\ \vdots \\ f(HL_{n,1}, HL_{n,2}, \cdots, HL_{n,m}) \end{bmatrix}
\]

(15)

where \( f(H_{\text{ANTLION}}) \) is the vector for the fitness value for all antlions, and \( f \) is the objective function.

2) ANTS RANDOM WALK

Since ants in nature move at random while searching for food, this movement is modeled as follows:

\[
R^t = [0, CS (2r (t_1) - 1), CS (2r (t_2) - 1), \ldots, CS (2r (t_{\text{max}}) - 1)]
\]

(16)

where \( CS \) indicates the cumulative summation of steps at each iteration, \( t_{\text{max}} \) is the maximum number of iterations, \( t \) denotes the current iteration defined as:

\[
r(t) = \begin{cases} 
1, & \text{if } \text{rand} > 0.5 \\
0, & \text{if otherwise}
\end{cases}
\]

(17)

where rand is a random number between 0 and 1.

\[
\text{Kernel} = \begin{bmatrix} k_0(0, p) & k_1(0, p) & \cdots & k_{l-1}(0, p) \\
k_0(1, p) & k_1(1, p) & \cdots & k_{l-1}(1, p) \\
k_0(2, p) & k_1(2, p) & \cdots & k_{l-1}(2, p) \\
\vdots & \vdots & \ddots & \vdots \\
k_0(l-1, p) & k_1(l-1, p) & \cdots & k_{l-1}(l-1, p) \end{bmatrix}
\]

(9)

\[
\text{Kernels}_{8 \times 8} = \begin{bmatrix}
0.0016 & -0.0091 & 0.0339 & -0.0958 & 0.2142 & 0.3831 & 0.5418 & -0.5793 \\
0.0091 & -0.0432 & 0.1317 & -0.2879 & 0.4544 & -0.4741 & 0.1916 & 0.3072 \\
0.0339 & -0.1317 & 0.3088 & -0.4661 & 0.3845 & 0.0362 & -0.4352 & 0.1916 \\
0.0958 & -0.2879 & 0.4661 & -0.3504 & -0.1288 & 0.4224 & 0.0362 & -0.4741 \\
0.2142 & -0.4544 & 0.3845 & 0.1288 & -0.4080 & -0.1288 & 0.3845 & 0.4544 \\
0.3831 & -0.4741 & -0.0362 & 0.4224 & 0.1288 & -0.3504 & -0.4661 & -0.2879 \\
0.5418 & -0.1916 & -0.4352 & -0.0362 & 0.3845 & 0.4661 & 0.3088 & 0.1317 \\
0.5793 & 0.3072 & -0.1916 & -0.4741 & -0.4544 & -0.2879 & -0.1317 & -0.0432
\end{bmatrix}
\]

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3) CONVERGENCE OF ANT TOWARDS ANTLION
When ant is trapped in the pit, it slides towards the antlion, ant getting close to the antlion, so the boundary of search space decreases adaptively. This may be expressed as:

\[ u^t_i = \frac{u^t_i}{I} \]  \hspace{1cm} (18)
\[ l^t_i = \frac{l^t_i}{I} \]  \hspace{1cm} (19)

where \( u^t_i \) is upper bounded at \( t^{th} \) iteration, \( l^t_i \) is lower bound at \( t^{th} \) iteration, \( I \) denotes ratio defined as \( I = 10^{w \frac{t}{t_{\text{max}}}} \), where \( w \) is a constant defined as: \( w = 2 \) when \( t > 0.1t_{\text{max}} \), \( w = 3 \) when \( t > 0.5t_{\text{max}} \), \( w = 4 \) when \( t > 0.75t_{\text{max}} \), \( w = 5 \) when \( t > 0.9t_{\text{max}} \) and \( w = 6 \) when \( t > 0.95t_{\text{max}} \).

4) ANTLIONS’ TRAPS AFFECT ANTS
Random walks of each ant are affected by Antlions’ traps; either antlion selected using roulette wheel or elite antlion in all iterations. This assumption may be expressed mathematically in simple form as:

\[ u^t_i = H_{\text{ANTLION}}^i + u^t \]  \hspace{1cm} (20)
\[ l^t_i = H_{\text{ANTLION}}^i + l^t \]  \hspace{1cm} (21)

where \( u^t_i \) indicates upper bound for \( i^{th} \) ant in \( t^{th} \) iteration, \( l^t_i \) indicates a lower bound for \( i^{th} \) ant in iteration, \( u^t \) is the upper bound, \( l^t \) is the lower bound, and \( H_{\text{ANTLION}}^i \) is position \( j^{th} \) antlion position in \( t^{th} \) iteration.

5) ENSURE THE OCCURRENCE OF RANDOM WALKS
Since the position of ants changes at every iteration and search space has boundaries, so to guarantee that random walk remains inside the search space, we use the following equation:

\[ R^t_j = \frac{(R^t_j - x^t_j) \ast (u^t_j - l^t_j)}{(y^t_j - x^t_j)} + l^t_j \]  \hspace{1cm} (22)

where \( R^t_j \) indicates random walk of \( j^{th} \) dimension at \( t^{th} \) iteration, \( x^t_j \) indicates a minimum of random walk \( R^t_j \) for the \( j^{th} \) dimension and \( i^{th} \) ant, \( y^t_j \) indicates a maximum of random walk \( R^t_j \) for the \( j^{th} \) dimension and \( i^{th} \) ant, \( u^t_j \) is upper bound in \( j^{th} \) dimension at \( t^{th} \) iteration, and \( l^t_j \) is lower bound in \( j^{th} \) dimension at \( t^{th} \) iteration.

6) RANDOM WALKS AROUND ELITE AND SELECTED ANTLION
As explained above, the better antlion, the higher chance of catching ant, the roulette wheel is used to select the fittest antlion. On the other hand, each iteration produces the best antlion. So the movement of ants is affected by elite antlion and a selected antlion using a roulette wheel. Ant walks randomly around \( H(\text{elite})_{\text{ANTLION}} \) and \( H(\text{selected})_{\text{ANTLION}} \) as:

\[ H_{\text{ANT}}^i = \frac{R^t_{\text{selected}} + R^t_{\text{elite}}}{2} \]  \hspace{1cm} (23)

Algorithm 1 Accelerated Ant Lion Optimizer AALO
1. Generate randomly initial population of ants and antlions Eqs. (12) and (14).
2. Compute the fitness value of ants and antlions. Eqs. (13) and (15).
3. Determine antlion which has the best fitness as elite.
4. While termination criteria are not satisfied
5. For each ant
6. Determine an antlion using Roulette wheel selection.
7. Update \( l^t \) and \( u^t \) using Eqs. (18) and (19).
8. Calculate levy walk of ant around \( H(\text{elite})_{\text{ANTLION}} \) and \( H(\text{selected})_{\text{ANTLION}} \) using Eq. (25).
9. Update ant position using Eq. (27).
10. end for
11. Compute the fitness value of all ants.
12. Update the position of antlion by replacing it with its corresponding ant using Eq. (24).
13. Choose elite antlion with higher fitness.
14. End while
15. Return the best antlion (elite).

where \( H_{\text{ANT}}^i \) shows \( i^{th} \) ant position at \( t^{th} \) iteration, \( R^t_{\text{selected}} \) shows the random walk around selected antlion using roulette wheel at \( t^{th} \) iteration, \( R^t_{\text{elite}} \) shows the random walk around the elite at \( t^{th} \) iteration.

7) CATCHING ANTS
After catching and pulling it into the sand, antlion updates its position with the corresponding ant. This happens when an ant’s fitness is more than antlion’s fitness, this formulated as:

\[ H_{\text{ANT}}^i = H_{\text{ANT}}^i \text{ if } f(H_{\text{ANT}}^i) > f(H_{\text{ANTLION}}^i) \]  \hspace{1cm} (24)

where \( H_{\text{ANT}}^i \) indicates \( i^{th} \) ant position at \( t^{th} \) iteration. Where \( H_{\text{ANTLION}}^i \) indicates \( i^{th} \) ant position at \( t^{th} \) iteration.

C. DESCRIPTION ACCELERATION ANT LION OPTIMIZER (AALO)
1) CONCEPT OF LEVY FLIGHT
Levy flight is a random walk in which the step length is not constant, but it is determined from levy distribution. Levy distribution has infinite variance and infinite mean with power low step size. Levy distribution is helpful for stochastic algorithms, and it has a role in exploration and exploitation [49]. Levy flight expressed mathematically as:

\[ \text{levywalk} = 0.01 \times \frac{x}{|y|^\alpha} \]  \hspace{1cm} (25)

where \( x \) and \( y \) are random numbers drawn from the normal distribution.

\[ x \sim N(0, \sigma_x^2), \hspace{1cm} y \sim N(0, \sigma_y^2) \]  \hspace{1cm} (26)
where

\[
\sigma_x = \left( \frac{\Gamma (1 + \beta) \times \sin \left( \frac{\pi \beta}{2} \right)}{\Gamma \left( \frac{1+\beta}{2} \right) \times \beta \times 2^{\frac{\beta-1}{2}} \right)^{1/\beta}, \quad \sigma_y = 1,
\]

\[
\Gamma (n) = (n - 1)! \quad \text{and} \quad 0 < \beta \leq 2.
\]

\[
H_{\text{ANT}_i} = \frac{L_{\text{selected}}^i + L_{\text{elite}}^i}{2}
\]

where \(H_{\text{ANT}_i}^i\) shows \(i^{th}\) ant position at \(i^{th}\) iteration, \(L_{\text{selected}}^i\) shows the levy walk around selected antlion using roulette wheel at \(i^{th}\) iteration, \(L_{\text{elite}}^i\) shows levy walk around the elite at \(i^{th}\) iteration.

2) ACCELERATION ALO ALGORITHM (AALO)

AALO is the improved form of the original ALO, where a random walk in ALO is replaced by levy flight. The AALO algorithm is represented in a simple form as follow:

IV. THE PROPOSED COMPRESSION ALGORITHM

The proposed algorithm uses the Krawtchouk moments to extract the ECG signal features. Then the AALO algorithm selects the optimum features that result in the best quality for signal reconstruction. ECG signal of size \((1 \times L)\) is divided into blocks of size \((1 \times l)\) as shown in Fig. 3a, where Krawtchouk moments for each block are computed using Eq. (10) to obtain coefficients. For the \((1 \times l)\) block, total \(l\) coefficients are obtained where the positions of these coefficients indicate possible solutions to the optimization problem. The objective function which evaluates these solutions is mean square error (MSE), where the coefficients with the minimum MSE are selected. MSE is calculated as follows:

\[
MSE = \frac{1}{l} \times \sum_{i=0}^{l-1} (s(x) - S(x))^2
\]

where \(l\) represents the signal block length, \(s(x)\) indicates the original signal block, and \(S(x)\) indicates a reconstructed signal block.
That is to say, the optimum solution (positions of coefficients) is one that minimizes the MSE (highest fitness value) between the original and reconstructed signal block. This process is shown in Fig. 3b. The required number of coefficients (RNC) is determined based on the desired compression ratio (CR) for signal reconstruction. This RNC is determined from among each block’s optimal coefficients. The optimum coefficients are used to reconstruct each block, as shown in Figure 3c. The following equation calculates RNC:

$$\text{RNC} = \text{Round} \left( \left( 1 - \frac{\text{CR}}{100} \right) \times l \right)$$  \hspace{1cm} (29)

After selecting optimum coefficients for each block, concatenate it to obtain the compressed signal, as illustrated in Fig. 3d. The compressed signal is divided into blocks according to the desired block size concerning the decompression phase. Then inverse transform is applied to each block using Eq. (11) to obtain the reconstructed signal. The selection process of the optimum coefficients using AALO algorithm is as follows:

1) A random population of solutions is generated, including random positions of coefficients (the length of each population is equal to RNC and contains a random value from 1 to \( l \) if block size = \( l \)).

2) Evaluate the solutions according to the objective function (MSE), and then the phases of AALO algorithm are applied until stopping criteria are met to get the best solution.

3) Select the optimum coefficients whose positions are the value in the best solution.

The Flowchart diagram of the compression and decompression processes of the proposed algorithm is illustrated in Fig. 4.

The proposed algorithm can be summarized (from steps 1 to 7 shows compression processes, and steps 8 to 11 illustrate decompression processes) in Algorithm 2.

V. EXPERIMENTAL RESULTS
All algorithms were tested using Matlab Software (version R2014a) on Microsoft Windows 7, 32-bit Edition, Intel Core i3 processor, 4 GB RAM machine.
Algorithm 2 The Proposed Compression Algorithm

1. Input the biomedical signal to be compressed (ECG).
2. Input size of the block (l) and determine the desired CR.
3. Compute the required number of coefficients (RNC) using Eq. (29).
4. Set the AALO algorithm parameters as follows: problem dimension (D) = RNC; Lower bounded (minimum position of the coefficient) = 1; Upper bounded (maximum position of the coefficient) = l;
5. Split the signal into (1x l)-sized blocks.
6. For each block
   6.1 Apply the block-based forward Krawtchouk transform to obtain the moment coefficients using Eq. (10).
   6.2 Select the optimum coefficients using AALO as follows:
      (a) Generate randomly initial population of ants and ant lion, and compute the fitness value by MSE.
      (b) Determine antlion which has the best fitness as elite.
      (c) For each ant, select an antlion using Roulette wheel selection and Update \(t^l\) and \(u^l\) using Eqs. (18) and (19).
      (d) Using Eq. (25), compute levy walk of ant around \(H_{elit\text{-}ANTLION}\) and \(H_{selected\text{-}ANTLION}\) and update the ant position using Eq. (27)
      (e) Compute the fitness value of all ants by MSE and Replace antlion with its matching ant to update its position using Eq. (24), Then Select the best antlion with higher fitness.
      (f) Repeat steps from (c) to (e) until the maximum iterations are reached.
      (g) Select only the coefficients whose positions are the values in the best solution (optimum coefficients) from the coefficients obtained in step 6.1, and set the other coefficients to zero.
7. Concatenate optimum coefficients for each block to obtain the compressed signal.
8. Divide the compressed signal into blocks.
9. Apply the block-based inverse Krawtchouk transforms on the optimum coefficients for each block using Eq. (11).
10. Combine the blocks to obtain the reconstructed signal.
11. Calculate the PRD, SNR, PSNR, and QS to evaluate the efficiency of the algorithm.

A. DATASETS

Performance evaluation of the proposed compression algorithm has been done by two distinct benchmark datasets, which contain ECG signals are acquired from the records of several people of various ages and under various conditions. Set the search agent = 3 and maximum iteration = 10 in the AALO algorithm.

1) MIT-BIH arrhythmia [50] is the first dataset that contains 48 ECG recordings. It is used to evaluate the compression methods’ performance. This database is extensively used to evaluate ECG compression and QRS detection algorithms because it has a variety of noise sources and arrhythmic QRS complex forms. Additionally, the database provides annotations for all R peaks in ECG signals. It has 48 ambulatory ECG recordings lasting half an hour. These recordings were obtained at a sampling frequency of 360 Hz (360 samples per second) with 11-bit resolution. This database is used to train the proposed algorithm and compare it to previously reported methods for ECG compression.

2) ECG-ID [51] is the second dataset which contains 310 ECG recordings obtained from 90 volunteers (44 men and 46 women aged 13 to 75 years). This dataset was gathered to assist research on using the electrocardiogram (ECG) for biometric identification. Signals in this dataset were obtained at a sampling frequency of 500 Hz (500 samples per second) with 12-bit resolution. Each recording includes ten annotated beats (unaudited R- and T-wave peaks annotations from an automated detector) and information containing age, gender, and recording date.

B. PERFORMANCE EVALUATION METRICS

The proposed compression algorithm’s performance and efficiency evaluation are estimated by the following performance criteria, which are described in [37] and [52]

- Compression ratio (CR)
  \[ CR = \frac{\text{size of the original signal in bit}}{\text{size of the compressed signal in bit}} \]  
  (30)
- Percent root mean square difference (PRD)
  \[ \text{PRD} = \sqrt{\frac{\sum (s(x) - \bar{s}(x))^2}{\sum s(x)^2}} \times 100 \]  
  (31)
  where \(s(x)\) is the original signal, and \(\bar{s}(x)\) is the reconstructed signal.

- Quality score (QS) QS is used to evaluate the compression method’s overall performance. High QS indicates good compression performance, which is presented as follows:
  \[ QS = \frac{CR}{PRD} \]  
  (32)
- Signal to noise ratio (SNR)
  SNR measures the amount of noise energy added into a signal due to compression and decompression procedures. It is presented as follows:
  \[ \text{SNR} = 10 \times \log \left(\frac{\sum (s(x) - \bar{s}(x))^2}{\sum (s(x) - \bar{\bar{s}}(x))^2}\right) \]  
  (33)
  where \(\bar{s}(x)\) is the mean value of \(s(x)\).
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TABLE 1. Result of the proposed compression algorithm on MIT-BIH arrhythmia dataset.

| NO | CR  | PRD  | SNR  | PSNR  | QS  |
|----|-----|------|------|-------|-----|
| 100 | 25  | 0.812 | 41.753 | 43.366 | 30.59 |
| 101 | 25  | 0.936 | 40.650 | 41.2599 | 26.88 |
| 102 | 20  | 1.1452 | 38.837 | 37.6746 | 17.49 |
| 103 | 18.18 | 0.9595 | 46.542 | 41.0838 | 19.35 |
| 104 | 22.22 | 1.2925 | 37.771 | 35.542 | 17.19 |
| 105 | 16.6 | 1.1314 | 38.927 | 37.8557 | 14.67 |
| 106 | 20  | 0.10250 | 39.785 | 39.5710 | 19.51 |
| 107 | 28.57 | 1.8899 | 34.471 | 28.942 | 15.11 |
| 108 | 20  | 1.7937 | 34.923 | 29.8301 | 11.15 |
| 109 | 25  | 0.5291 | 45.529 | 51.0576 | 47.25 |
| 111 | 22.22 | 1.0842 | 39.297 | 38.5985 | 20.49 |
| 112 | 28.5 | 0.9417 | 40.521 | 41.0422 | 30.26 |
| 113 | 33.33 | 0.0450 | 39.617 | 39.2361 | 31.89 |
| 114 | 15.38 | 0.0471 | 47.805 | 55.6135 | 37.78 |
| 115 | 20  | 1.1926 | 38.870 | 36.9366 | 16.77 |
| 116 | 40  | 1.2648 | 39.454 | 38.9099 | 37.56 |
| 117 | 25  | 1.1104 | 39.999 | 38.1814 | 22.51 |
| 118 | 25  | 1.0982 | 38.186 | 38.3734 | 22.76 |
| 119 | 25  | 1.1671 | 38.657 | 37.3160 | 21.42 |
| 121 | 33.33 | 1.3127 | 37.636 | 35.2731 | 25.39 |
| 122 | 25  | 1.9933 | 39.225 | 38.4507 | 22.86 |
| 123 | 16.6 | 1.2590 | 39.576 | 39.1524 | 15.80 |
| 124 | 25  | 1.2967 | 37.743 | 35.4858 | 19.27 |
| 200 | 20  | 0.5665 | 44.936 | 49.8722 | 35.30 |
| 201 | 25  | 0.9383 | 40.553 | 41.1065 | 26.64 |
| 202 | 20  | 2.6602 | 31.501 | 23.0035 | 7.92 |
| 203 | 20  | 0.5569 | 45.084 | 50.1698 | 35.91 |
| 205 | 20  | 1.3644 | 37.678 | 35.3567 | 15.30 |
| 207 | 20  | 0.5195 | 45.688 | 51.3780 | 38.49 |
| 208 | 28.57 | 0.8428 | 41.485 | 42.9717 | 33.89 |
| 209 | 16.66 | 0.6035 | 43.484 | 48.7731 | 27.60 |
| 210 | 25  | 0.5614 | 45.014 | 50.0279 | 44.53 |
| 211 | 25  | 0.8514 | 41.597 | 42.7994 | 29.36 |
| 213 | 25  | 0.7127 | 42.941 | 45.8835 | 35.97 |
| 214 | 25  | 0.4022 | 47.911 | 55.8227 | 62.16 |
| 215 | 22.22 | 0.4070 | 47.808 | 56.6156 | 54.59 |
| 217 | 20  | 0.3992 | 47.976 | 55.9531 | 50.10 |
| 219 | 28.5 | 0.4049 | 47.853 | 55.7051 | 70.38 |
| 220 | 25  | 1.3749 | 37.234 | 34.4961 | 18.18 |
| 221 | 25  | 0.9275 | 46.655 | 41.3067 | 26.95 |
| 222 | 25  | 0.5491 | 45.206 | 50.4150 | 45.52 |
| 223 | 22.22 | 1.2995 | 37.724 | 35.4848 | 17.09 |
| 228 | 33.33 | 1.0057 | 39.950 | 39.9018 | 33.14 |
| 230 | 28.5 | 0.8143 | 41.784 | 43.5609 | 34.99 |
| 231 | 20  | 0.8270 | 44.954 | 48.1087 | 31.89 |
| 232 | 25  | 1.3406 | 39.654 | 39.3079 | 24.03 |
| 233 | 25  | 0.5953 | 44.505 | 49.0096 | 41.99 |
| 234 | 25  | 0.5140 | 45.780 | 51.5629 | 48.63 |
| Avg | 23.96 | 0.95 | 41.22 | 42.43 | 29.86 |

• Peak signal to noise ratio (PSNR) PSNR is the greatest possible signal power ratio to the corrupting noise power. It is formulated as follows:

$$\text{PSNR} = 20 \times \log_{10} \frac{|s(x)|}{\sqrt{MSE}} \tag{34}$$

• Compression Speed

The term “Compression Speed” refers to the amount of uncompressed data that may be compressed in a single second. Equations (35) and (36) specify the compression and decompression speeds, respectively.

Compression Speed = \frac{\text{uncompressed bits}}{\text{Seconds to compress}} \tag{35}

Decompression Speed = \frac{\text{uncompressed bits}}{\text{Seconds to decompress}} \tag{36}

• Computational efficiency (CE) The Computational efficiency of the compression algorithm is computed with CE. A high CE value indicates that the compression technique has a high CR and a minimal processing time. Computational efficiency (CE) is defined as:

$$\text{CE} = \frac{\text{CR}}{\text{Processing Time}} \tag{37}$$

C. RESULTS ON MIT-BIH ARRHYTHMIA DATASET

As shown in Table 1, the proposed compression algorithm is tested on the Whole (48 record) MIT-BIH arrhythmia ECG dataset, with various compression ratios. Table 1 indicates that the proposed algorithm achieves excellent results on all records in the dataset, which provides high compression ratios (CR) with very good reconstruction quality (PRD), in addition to excellent SNR, PSNR. For example, records 217, 215, 214, 219 have the highest Quality Score (QS) 70.38, 62.16, 54.59, 50.10, respectively (A high QS result means a large CR accompanied by a low distortion rate). The average performance of the proposed algorithm in terms of CR, PRD, SNR, PSNR, and QS are 23.96, 0.95, 41.22, 42.43, and 29.86, respectively, as reported in Table 1.

Figs. 5, 6, and 7 show samples of ECG signals compressed and decompressed using the proposed algorithm. Visual inspection reveals that the reconstructed signals are very much identical to original signals. To verify the efficiency of the proposed algorithm, a comparison with existing algorithms is performed, as shown in Table 2.
FIGURE 5. Compression of MIT-BIH record 100 with CR = 25 and PRD = 0.817.

FIGURE 6. Compression of MIT-BIH record 114 with CR = 15.38 and PRD = 0.407.

FIGURE 7. Compression of MIT-BIH record 228 with CR = 33.3 and PRD = 1.005.

compression algorithms [23], [31], [34], [37], [39], [53], and [54] is made in terms of CR, PRD, and QS as illustrated in Table 2.

Fig. 8 displays a comparison of the proposed algorithm’s performance with other existing compression algorithms [43], [28], [55], and [56] concerning the CR-PRD results using MIT-BIH arrhythmia dataset. Results in Table 2 and Fig. 8 show the superiority of the proposed algorithm over the other algorithms, which it has very high CR and the lowest PRD values, Hence the highest QS. As a result, the proposed algorithm provides the highest reconstructed signal quality compared to the other existing methods.

D. RESULTS ON ECG-ID DATASET

Table 3 present the compression performance of the proposed algorithm using ECG-ID dataset. Tables 3 illustrate the resulting CR and PRD, SNR, PSNR, and QS performance metrics for 10 records from ECG-ID dataset. The compression is done at different CRs (5, 6.66, and 10), which achieve the best results in PRD, SNR, and PSNR and excellent reconstruction
quality. As shown in Table 3, average performance of the proposed algorithm in terms of CR, PRD, SNR, PSNR, and QS are 7.16, 0.43, 47.83, 55.65, and 17.98, respectively. The proposed algorithm’s performance is compared to other algorithms in the literature in terms of CR, PRD, and QS, as shown in Table 4.

As reported in Table 4, for Person 02/rec1 signal DEZW algorithm [56] has the highest performance in terms of CR = 21.78 but does not provide the best value of PRD = 9.24. Hence the information of diagnostic can be lost. On the contrary, the proposed algorithm has a low value in CR = 4 but provides very good PRD = 0.4462. This ensures that no loss in diagnostic information when the signal is reconstructed. Concerning Person 03/rec1 signal at the same CR = 5, the proposed algorithm outperforms in value of PRD = 0.3423. Fig. 9 and 10 display the compression of Person 01/rec1 and Person 02/rec1 signals by the proposed algorithm.
TABLE 3. Result of the proposed compression algorithm on ECG-ID dataset.

| No | CR  | PRD | SNR  | PSNR | QS |
|----|-----|-----|------|------|----|
| Person 01/rec1 | 6.66 | 0.6855 | 43.279 | 46.5597 | 9.71 |
| Person 01/rec5 | 10 | 0.7226 | 42.822 | 45.8446 | 13.83 |
| Person 01/rec20 | 5 | 0.9253 | 49.796 | 59.514 | 15.37 |
| Person 02/rec1 | 10 | 0.4462 | 47.009 | 54.0175 | 22.41 |
| Person 02/rec10 | 10 | 0.3429 | 49.296 | 58.5955 | 29.16 |
| Person 02/rec21 | 5 | 0.2211 | 53.108 | 66.2128 | 22.62 |
| Person 03/rec1 | 10 | 0.3423 | 49.311 | 58.6258 | 29.22 |
| Person 04/rec1 | 5 | 0.4572 | 46.797 | 53.5963 | 10.94 |
| Person 05/rec1 | 5 | 0.3756 | 49.434 | 58.8709 | 14.82 |
| Person 06/rec1 | 5 | 0.4250 | 47.832 | 54.8630 | 11.76 |
| Avg. | 7.16 | 0.43 | 47.83 | 55.65 | 17.98 |

TABLE 4. Comparison of the proposed algorithm and other algorithms in terms of CR, PRD and QS on the ECG-ID dataset.

| Techniques | ECG record | CR  | PRD | QS       |
|------------|------------|-----|-----|----------|
| MEZW [56]  | Person 02/rec1 | 8.53 | 6.55 | 1.30     |
| SPHT [56]  | 9.77 | 6.48 | 1.507 |
| DEZW [56]  | 21.78 | 9.24 | 2.727 |
| Tchebichef+ABC [43] | 20 | 8.53 | 2.344 |
| proposed algorithm | 4 | 0.4462 | 8.964 |
| MEZW [56]  | Person 03/rec1 | - | - | -        |
| SPHT [56]  | - | - | -     |
| DEZW [56]  | - | - | -     |
| Tchebichef+ABC [43] | 5 | 2.764 | 1.8089 |
| proposed algorithm | 5 | 0.3423 | 14.60 |

TABLE 5. Results of the proposed algorithm in terms of the processing time, computational efficiency, and Compression speed on two datasets.

| ECG signal | CR  | Processing Time(s) | Compression Speed(bps) | CE  |
|------------|-----|---------------------|------------------------|-----|
| 101        | 25  | 7.30                | 3945.20                | 3.42 |
| 118        | 25  | 6.50                | 4430.76                | 3.84 |
| 124        | 25  | 6.70                | 4298.50                | 3.73 |
| 200        | 20  | 5.90                | 4821.35                | 3.23 |
| 205        | 20  | 6.40                | 4500.00                | 3.12 |
| 214        | 25  | 6.30                | 4571.42                | 3.96 |
| 217        | 20  | 5.60                | 5142.85                | 3.57 |
| 221        | 25  | 6.40                | 4500.00                | 3.90 |
| 230        | 28.5| 6.15                | 4682.92                | 4.63 |
| 234        | 25  | 6.45                | 4465.11                | 3.87 |
| Person 01/rec1 | 6.66 | 5.40 | 4761.90 | 0.79 |
| Person 02/rec1 | 10 | 8.10 | 4938.27 | 1.23 |
| Person 03/rec1 | 10 | 7.96 | 5025.12 | 1.25 |
| Person 06/rec1 | 5 | 8.30 | 4819.27 | 0.59 |
| Avg.      | 19.29 | 6.89 | 4640.19 | 2.95 |

F. ENERGY CONSUMPTION EVALUATION

In this part, we introduce a method to evaluate energy consumption. Before introducing the method, we state some notes.

- When processing or transmitting data, wearable devices are in a ‘wake-up’ state; when not, they are in a ‘sleep’ state.
- When a wearable device is in a ‘wake-up’ mode, it consumes its battery for the duration of that period.
- The proposed algorithm reduces battery consumption by decreasing the transmitting data size because the transmitting data time is reduced.
- Because the algorithm increases the processing time, which leads to increased energy consumption.
- So, there is some trade-off between transmission time and processing time.

In order to verify the outperform of the proposed algorithm in the processing time, Compression speed, and computational efficiency, a comparison with Tchebichef+ABC [43] is made and illustrated in Table 6, Fig. 11,12. As shown in Table 6, Figs. 11, 12, the superiority of the proposed algorithm in processing time, and thus compression speed, and computational efficiency. That superiority is due to the accelerated Ant Lion Optimizer (AALO) algorithm using levy flight; this acceleration reduced the number of iterations performed by AALO algorithm in the process of searching for the optimum solutions.

E. COMPRESSION SPEED AND COMPUTATIONAL EFFICIENCY

The processing time, Compression speed, and computational efficiency for different signals from the two datasets used in this paper applied on the proposed algorithm are reported in Table 5. Processing time and compression speed associated with the proposed algorithm are equally important as their compression performance.

The algorithm’s speed in compression is vital in being appropriate for wireless biosensors in Remote Monitoring Systems. The less processing time, the higher the Compression speed and computational efficiency, as shown in Table 5.
TABLE 6. The processing time and the computational efficiency results of the proposed algorithm compared with Tchebichef + ABC algorithm on MIT-BIH arrhythmia dataset.

| ECG signal | Tchebichef ABC[34] | proposed algorithm |
|------------|--------------------|-------------------|
|            | CR | Processing Time(s) | Compression Speed(bps) | CE  | CR | Processing Time(s) | Compression Speed(bps) | CE  |
| 100        | 2  | 73.804             | 390.22              | 0.027| 2  | 5.41              | 5323.47             | 0.369|
|            | 4  | 72.322             | 398.21              | 0.155| 4  | 5.78              | 4982.69             | 0.392|
|            | 8  | 69.342             | 415.33              | 0.115| 8  | 6.50              | 4430.76             | 1.174|
| 101        | 2  | 72.992             | 394.56              | 0.027| 2  | 5.70              | 5502.63             | 0.350|
|            | 4  | 71.791             | 401.16              | 0.055| 4  | 6.30              | 4571.42             | 0.634|
|            | 8  | 72.010             | 399.94              | 0.111| 8  | 6.90              | 4173.91             | 1.159|

- Let X is the time the original signal needed to transmit, and Y is the time-compressed signal required to be compressed and transmitted.
- Since Bluetooth typically sends one packet per second [57], the database used here is 360 HZ (360sample per second); for example, signal MIT-BIH Rec. 100 is ten packets (10×360 = 3600 samples), so it needs ten seconds (10,000 ms) to transmit.
- Using the proposed algorithm, if the signal is compressed with CR = 10, it will be 360sample (1 packet) and need 1 second to transmit, but the compression time is 5400 ms.

The previous table shows that the wearable device takes 10,000 ms seconds to send the signal without compression. Still, in using the proposed algorithm, the device takes 5400 ms seconds to compress the signal and 1 second (1000 ms) to send it, so the wearable device takes(1000 ms+5400 ms) 6400 ms to compress and send the signal. The meaning of it The overall work time decreases by about 3600ms seconds, thereby reducing the battery consumption of the wearable device.

VI. DISCUSSION

The comparative experiments and the above results show that the proposed compression algorithm is superior to other existing methods. The proposed algorithm is numerically evaluated on two widely used datasets. The experiments included many performance measures. Firstly, compression ratio and reconstruction quality. Secondly, compression speed and computational efficiency. The last direction is energy consumption. The tabular and graphical results show the effectiveness of the proposed algorithm in all directions performance measures. The performance indices’ average value is CR = 23.96, PRD = 0.95, SNR = 41.22, PSNR = 42.43, QS = 29.86 on MIT-BIH arrhythmia ECG dataset. Regarding ECG-ID dataset the average value are; CR = 7.16, PRD = 0.43, SNR = 47.83, PSNR = 55.65, QS = 17.98. Although the proposed method did not achieve the highest CR, he did obtain the best PRD, SNR, PSNR, and QS. This ensures no loss in diagnostic information when the signal is reconstructed; it is critical when compressing medical signals since any loss of diagnostic data results in an incorrect diagnosis. In addition, the proposed algorithm’s superiority in terms of processing time and thus compression speed and computational efficiency make it more effective in reducing energy consumption. The superiority of the proposed algorithm in compression ECG signals is due to the following worthwhile reasons:

1. Krawtchouk moments are orthogonal moments with orthogonal basis functions. Thus, each krawtchouk moment coefficient can capture distinct and unique parts of the signal with no information redundancy.
2. Krawtchouk moments’ basis functions can extract various distinct types of information from the signal depending on the order value.
3. Moments based on discrete orthogonal polynomials are good in signal compression. It is because they exhibit better energy compaction for common signals. If a discrete orthogonal moment is properly chosen, the energy in the signal will be concentrated on a relatively small percentage of the moment coefficients; these coefficients are stored and then later used for generating the reconstructed signal.
4. The ability of Krawtchouk moments on local and global feature extraction.
5. The superior compression speed and computational efficiency result from the accelerated Ant Lion Optimizer (AALO) algorithm using levy flight; this acceleration lowered the number of iterations conducted by the AALO algorithm when searching for the optimal solution.

While several compression techniques have been developed, considerable limitations and challenges remain. In designing compression methods, computational complexity and accessible memory management play a critical role. The majority of existing techniques are computational complexity, especially in real-time applications such as Remote Monitoring Systems. Memory management becomes more difficult with the use of compression algorithms. When the memory required to conduct the compression technique exceeds the available device memory, efficient compression cannot be accomplished. Even though some compression techniques achieve higher CR, they do not efficiently manage usable memory. As a result, memory management in compression algorithms is another interesting study area.
VII. CONCLUSION
The present article proposes an efficient ECG signal compression algorithm using discrete krawtchouk moments and AALO. The numerous experiments of the proposed algorithm are applied to two commonly used datasets; the MIT-BIH arrhythmia dataset and the ECG-ID dataset. The proposed algorithm’s performance was evaluated in three directions. The first direction is compression ratio and reconstruction quality. The second is compression speed and computational efficiency. The last direction is energy consumption. The comparative experiments indicate the proposed algorithm’s advantage compared to other compression algorithms in all directions. This performance improvement in the proposed algorithm is due to orthogonal Krawtchouk moments to extract the features from ECG signals. In addition, using the AALO algorithm successfully selects the best krawtchouk moments based on the MSE as an objective function in the proposed algorithm. The selection of the optimum krawtchouk moments using AALO gives improved high-quality reconstructed ECG signals in a reasonable time. This is because AALO finds the optimal feature in less number of iterations, decreasing the processing time and, consequently, energy consumption. From the research that has been performed, it is possible to conclude that the proposed algorithm achieves a high compression ratio, preserving the reconstructed signal’s quality and reducing energy consumption. Thus, it is suitable for wearable sensors and processing long-term recordings and huge databases and Remote Health Monitoring Systems. In our future research, the ability of the proposed algorithm in compression could be increased by using new Discrete Orthogonal Moments as a feature extractor to obtain features from the ECG signal. Furthermore, using different feature selection algorithms to select the optimum features that achieve the best-reconstructed signal can be a highly effective strategy for optimizing the algorithm’s ability in compression.

REFERENCES
[1] S. S. Virani et al., “Heart disease and stroke statistics-2020 update: A report from the American Heart Association,” Circulation, vol. 141, no. 9, pp. e139–e259, 2020.
[2] V. Gupta, M. Mittal, V. Mittal, and N. K. Saxena, “A critical review of feature extraction techniques for ECG signal analysis,” J. Inst. Eng. India B, vol. 102, no. 5, pp. 1049–1060, Oct. 2021.
[3] M. Elgendi, M. Jonkman, and F. De Boer, “Improved QRS detection algorithm using dynamic thresholds,” Int. J. Hybrid Inf. Technol., vol. 2, no. 1, pp. 65–80, 2009.
[4] A. F. Hussein, N. A. Kumar, M. Burbano-Fernandez, G. Ramirez-Gonzalez, E. Abdulhay, and V. H. C. De Albuquerque, “An automated remote cloud-based heart rate variability monitoring system,” IEEE Access, vol. 6, pp. 77055–77064, 2018.
[5] C. Venkatesan, P. Karthigaikumar, and S. Satheeskumaran, “Mobile cloud computing for ECG telemonitoring and real-time coronary heart disease risk detection,” Biomed. Signal Process. Control, vol. 44, pp. 138–145, Jul. 2018.
[6] B. R. Stojkoska and Z. Nikolovski, “Data compression for energy efficient IoT solutions,” in Proc. 25th Telecommun. Forum (TELFOR), Nov. 2017, pp. 1–4.
[7] Z. Rezaei and S. Mobininejad, “Energy saving in wireless sensor networks,” Int. J. Comput. Sci. Eng. Surv., vol. 3, no. 1, p. 23, 2012.
[8] C. Li, X. Yuan, L. Yang, and Y. Song, “A hybrid lifetime extended directional approach for WBANs,” Sensors, vol. 15, no. 11, pp. 28005–28030, 2015.
[9] S. Kim and B. K. Song, “A prioritized resource allocation algorithm for multiple wireless body area networks,” Wireless Netw., vol. 23, no. 3, pp. 727–735, Apr. 2017.
[10] R. Kumar, A. Kumar, and R. K. Pandey, “Beta wavelet based ECG signal compression using lossless encoding with modified thresholding,” Comput. Electr. Eng., vol. 39, no. 1, pp. 130–140, Jan. 2013.
[11] A. Bendifallah, R. Benzid, and M. Boulemden, “Improved ECG compression method using discrete cosine transform,” Electron. Lett., vol. 47, no. 2, pp. 87–89, Jan. 2011.
[12] J. Ma, T. Zhang, and M. Dong, “A novel ECG data compression method using adaptive Fourier decomposition with security guarantee in e-health applications,” IEEE J. Biomed. Health Inform., vol. 19, no. 3, pp. 986–994, May 2015.
[13] A. Al-Shrouf, M. Abe-Zahhad, and S. M. Ahmed, “A novel compression algorithm for electrocardiogram signals based on the linear prediction of the wavelet coefficients,” Digit. Signal Process., vol. 13, no. 4, pp. 604–622, Oct. 2003.
[14] M. S. Hossain and N. Amin, “ECG compression using subband thresholding of the wavelet coefficients,” Austral. J. Basic Appl. Sci., vol. 5, no. 5, pp. 739–749, 2011.
[15] A. Kumar, M. Kumar, and R. Komaragiri, “Design of a biothogonal wavelet transform based R-Peak detection and data compression scheme for implantable cardiac pacemaker systems,” J. Med. Syst., vol. 42, no. 6, pp. 1–12, Jun. 2018.
[16] C. K. Jha and M. H. Kolekar, “Diagnostic quality assured ECG signal compression with selection of appropriate mother wavelet for minimal distortion,” IET Sci., Meas. Technol., vol. 13, no. 4, pp. 500–508, Jun. 2019.
[17] C. K. Jha and M. H. Kolekar, “Classification and compression of ECG signal for Holter device,” in Biomedical Signal and Image Processing in Patient Care, Hershey, PA, USA: IGI Global, 2018, pp. 46–63.
[18] C. K. Jha and M. H. Kolekar, “Efficient ECG data compression and transmission algorithm for telemedicine,” in Proc. 8th Int. Conf. Commun. Syst. Netw. (COMSNETS), Jan. 2016, pp. 1–6.
[19] M. Abo-Zahhad, S. M. Ahmed, and A. Zakaria, “An efficient technique for compressing ECG signals using QRS detection, estimation, and 2D DWT coefficients thresholding,” Model. Simul. Eng., vol. 2012, pp. 1–10, Jun. 2012.
[20] S.-C. Tai, C. Sun, and W.-C. Yan, “A 2-D ECG compression method based on wavelet transform and modified SPIHT,” IEEE Trans. Biomed. Eng., vol. 52, no. 6, pp. 999–1008, Jun. 2005.
[21] J.-J. Wei, C.-J. Chang, N.-K. Chou, and G.-J. Jan, “ECG data compression using truncated singular value decomposition,” IEEE Trans. Inf. Technol. Biomed., vol. 5, no. 4, pp. 290–299, Dec. 2001.
[22] B. A. Rajoub, “An efficient coding algorithm for the compression of ECG signals using the wavelet transform,” IEEE Trans. Biomed. Eng., vol. 49, no. 4, pp. 355–362, Apr. 2002.
[23] M. Pooyan, A. Taheri, M. Moazami-Goudarzi, and I. Saboori, “Wavelet compression of ECG signals using SPIHT algorithm,” Int. J. Signal Process., vol. 1, no. 3, pp. 4, 2004.
[24] E. Sharifahmadian, “Wavelet compression of multichannel ECG data by enhanced set partitioning in hierarchical trees algorithm,” in Proc. Int. Conf. IEEE Eng. Med. Biol. Soc., Aug. 2006, pp. 5238–5243.
[25] M. Moazami-Goudarzi and M. H. Moradi, “Electrocardiogram signal compression using multiwavelet transform,” Signal Process., vol. 4, p. 12, 2005.
[26] C. K. Jha and M. H. Kolekar, “Electrocardiogram data compression using DCT based discrete orthogonal stockwell transform,” Biomed. Signal Process. Control, vol. 46, pp. 174–181, Sep. 2018.
[27] G. Tohumoglu and K. E. Sezgin, “ECG signal compression by multi-iteration EZW coding for different wavelets and thresholds,” Comput. Biol. Med., vol. 37, no. 2, pp. 173–182, Feb. 2007.
[28] R. Kumar, A. Kumar, and G. K. Singh, “Hybrid method based on singular value decomposition and embedded zero tree wavelet technique for ECG signal compression,” Comput. Methods Programs Biomed., vol. 129, pp. 135–148, Jun. 2016.
[29] M. Elgendi, A. Mohamed, and R. Ward, “Efficient ECG compression and QRS detection for e-health applications,” Sci. Rep., vol. 7, no. 1, pp. 1–16, Dec. 2017.
[30] J. Zhou and C. Wang, “An ultra-low power turning angle based biomedical signal compression engine with adaptive threshold tuning,” Sensors, vol. 17, no. 8, p. 1809, Aug. 2017.
R. Kumar, A. Kumar, and G. K. Singh, “Computationally efficient cosine modulated filter bank design for ECG signal compression,” *IRBM*, vol. 41, no. 1, pp. 2–17, Feb. 2020.

F. Wang, Q. Ma, W. Liu, S. Chang, H. Wang, J. He, and Q. Huang, “A novel ECG signal compression method using spindle convolutional autoencoder,” *Comput. Methods Programs Biomed.*, vol. 175, pp. 139–150, Jul. 2019.

J. Chagnon and L. Rebollo-Neira, “Mixed-transform based codec for 2D compression of ECG signals,” *Biomed. Signal Process. Control*, vol. 62, Sep. 2020, Art. no. 102067.

S. Chandra, A. Sharma, and G. K. Singh, “A comparative analysis of performance of several wavelet based ECG data compression methodologies,” *IRBM*, vol. 42, no. 4, pp. 227–244, Aug. 2021.

K. Khalidi and A.-O. Boudraa, “On signals compression by EMD,” *Electron. Lett.*, vol. 48, no. 21, pp. 1329–1331, 2012.

X. Wang, Z. Chen, J. Luo, J. Meng, and Y. Xu, “ECG compression based on combining of EMD and wavelet transform,” *Electron. Lett.*, vol. 52, no. 19, pp. 1588–1590, 2016.

C. K. Jha and M. H. Kolekar, “Empirical mode decomposition and wavelet transform based ECG data compression scheme,” *IRBM*, vol. 42, no. 1, pp. 65–72, Feb. 2021.

T.-H. Tsai and F.-L. Tsai, “Efficient lossless compression scheme for multi-channel ECG signal processing,” *Biomed. Signal Process. Control*, vol. 59, May 2020, Art. no. 101879.

L. Zheng, Z. Wang, J. Liang, S. Luo, and S. Tian, “Effective compression and classification of ECG arrhythmia by singular value decomposition,” *Biomed. Eng. Adv.*, vol. 2, Dec. 2021, Art. no. 100013.

C. K. Jha and M. H. Kolekar, “Electrocardiogram data compression techniques for cardiac healthcare systems: A methodological review,” *IRBM*, Jun. 2021.

K. M. Hosny, A. M. Khalid, and E. R. Mohamed, “Efficient compression of volumetric medical images using Legendre moments and differential evolution,” *Soft Comput.*, vol. 24, no. 1, pp. 409–427, Jan. 2020.

M. A. Elaziz, K. M. Hosny, and I. M. Selim, “Galaxies image classification using artificial bee colony based on orthogonal Gegenbauer moments,” *Soft Comput.*, vol. 23, no. 19, pp. 9573–9583, Oct. 2019.

K. M. Hosny, A. M. Khalid, and E. R. Mohamed, “Efficient compression of bio-signals by using Tchebichef moments and artificial bee colony,” *Bio-Systems: Biomed. Eng.*, vol. 38, no. 2, pp. 385–398, 2018.

R. Benouni, I. Batioua, K. Zenkouar, A. Zahi, S. Najah, and H. Qjidaa, “Fractional-order orthogonal Chebyshev moments and moment invariants for image representation and pattern recognition,” *Pattern Recognit.*, vol. 86, pp. 332–343, Feb. 2019.

A. Daoui, M. Yamni, O. El Ogri, H. Karmouni, M. Sayyouri, and H. Qjidaa, “Stable computation of higher order Charlier moments for signal and image reconstruction,” *Inf. Sci.*, vol. 521, pp. 251–276, Jun. 2020.

B. M. Mahmmod, A. M. Abdul-Hadi, S. H. Abdulhussain, and A. Hussien, “On computational aspects of Krawtchouk polynomials for high orders,” *J. Imag.*, vol. 6, no. 8, p. 81, Aug. 2020.

H. Zhu, M. Liu, H. Shu, H. Zhang, and L. Luo, “General form for obtaining discrete orthogonal moments,” *IET Image Process.*, vol. 4, no. 5, pp. 335–352, Oct. 2010.

S. Mirjalili, “The ant lion optimizer,” *Adv. Eng. Softw.*, vol. 83, pp. 80–98, May 2015.

C. T. Brown, L. S. Liebovitch, and R. Glendorn, “Lévy flights in dobe Ju ’hoansi foraging patterns,” *Hum. Ecol.*, vol. 35, no. 1, pp. 129–138, Feb. 2007.

[Online]. Available: https://www.physionet.org/physiobank/database/mitdb/

[Online]. Available: https://physionet.org/physiobank/database/ecgiddb/

L. Shaw, D. Rahman, and A. Routray, “Highly efficient compression algorithms for multichannel EEG,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 5, pp. 957–968, May 2018.

M. M. Abo-Zahhad, T. K. Abdel-Hamid, and A. M. Mohamed, “Compression of ECG signals based on DWT and exploiting the correlation between ECG signal samples,” *Int. J. Commun., Netw. Syst. Sci.*, vol. 7, no. 1, pp. 53–70, 2014.

R. Kumar, A. Kumar, and G. K. Singh, “Electrocardiogram signal compression based on singular value decomposition (SVD) and adaptive scanning wavelet difference reduction (ASWDR) technique,” *AEU, Int. J. Electron. Commun.*, vol. 69, no. 12, pp. 1810–1822, Dec. 2015.

A. Fathi and F. Faraji-Kheirabadi, “ECG compression method based on adaptive quantization of main wavelet packet subbands,” *Signal. Image Video Process.*, vol. 10, no. 8, pp. 1433–1440, Nov. 2016.

Z. Peng, G. Wang, H. Jiang, and S. Meng, “Research and improvement of ECG compression algorithm based on EZW,” *Comput. Methods Programs Biomed.*, vol. 145, pp. 157–166, Jul. 2017.

G.-Y. Cho, G.-Y. Lee, and T.-R. Lee, “Efficient real-time lossless EMG data transmission to monitor pre-term delivery in a medical information system,” *Appl. Sci.*, vol. 7, no. 4, p. 366, Apr. 2017.

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