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Enhancing EMG signal classification using convolution neural network optimized with fractional order bat algorithm

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Abstract The galvanizing activity of nerves and muscles, known as electromyograms (EMG), is a valuable diagnostic tool for identifying muscle and nerve disorders. Effective identification and classification of normal and abnormal EMG signals such as myopathies and Amyotrophic Lateral Sclerosis (ALS) plays a pivotal role in supporting computerized diagnostic tools, which is particularly important because of the non-stationary characteristic of EMG signals. Therefore, developing an efficient classification system for EMG signals is indispensable to facilitate the computer-assisted prediction of abnormalities. Initially, the smoothed pseudo-Wigner–Ville transform is employed to reconstruct the time series of EMG into time–frequency images. Convolution neural network (CNN) is reconstructed with fractional order bat optimization algorithm for classifying the EMG signals. The efficiency of the developed fractional order bat-CNN was compared with the bat-CNN. Results express that the CNN combined with fractional order bat optimization proves to be highly effective in accurately classifying normal and abnormal EMG images, achieving an accuracy rate of 99.11%. It is also proved that the unification of fractional order bat optimization in CNN has exhibited superior performance compared to CNN with bat optimization algorithm.

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Keywords Bat optimization · Convolution neural network · EMG · Fractional calculus · Smoothed pseudo-Wigner–Ville transform

1 Introduction

The neuromuscular disorder is an extensive range of conditions that affect the muscles or nervous system comprising the sensory and motor nerves that connect to the brain. The genesis for neuromuscular diseases includes genetic disorders, hormonal ailments, and autoimmune conditions. Spinal muscular atrophy, muscular dystrophy, and dysfunction of muscle fibre such as myopathy and ALS are various ailments that disrupt the functions of voluntary muscles [1, 2]. Neuromuscular disorders are categorized by the affected elements of the motor unit as follows: Myopathy is a condition of muscle fibre dysfunction. Myopathy can be congenital, or it can be acquired because of autoimmune conditions (myositis) [3]. Myopathies exhibit various indicators, which include low energy and fatigue, upper arm and thigh weakness, muscle soreness, weakness, numbness, cramps, etc.; ALS (neuropathy) is the degeneration of nerves, Charcot's or Lou Gehrig's disease; junctionopathies are the conditions affecting the nerve junctions; and neuronopathy is the neuron cell ailments [4].

EMG or electrodiagnostic study (EDS) is a diagnostic procedure to record the galvanizing activity of nerves and muscles for recognizing neuromuscular dysfunction [5]. An EMG procedure assists in identifying the response of muscles to nerve signals. EMG signals can be obtained using electrodes (invasive or non-invasive). The anomalous signals from the database are analysed which encompasses various deviations from typical muscle electrical activity, such as abnormalities linked to muscle and neuromuscular disorders, electrode-related problems, baseline drift, noise, movement artefacts, and external interference. Recognizing and understanding these anomalies is crucial for precise interpretation and diagnosis in both clinical and research settings involving EMG recordings. Therefore, an effective computer assisted model comprising various techniques such as attribute extraction, variable selection, and a trained classification model is necessary for investigating EMG signals [6]. Attribute extraction is a method to determine the features required for learning from the bio-signals obtained using EDS.

The analysis of EMG signals can be conducted in various domains, such as time, frequency, and time–frequency. The time–frequency feature holds notable advantages over time-domain and frequency features. It provides a detailed depiction of temporal dynamics, high-resolution frequency components of muscle activities, analysis of non-stationary signals through a time-varying depiction of frequency content, enhanced visualization, and adaptability. It offers a more comprehensive representation of muscle activity, improves the detection of muscle contractions, and ultimately enhances the overall performance of classification methods [7]. Elbeshbeshy et al. (2021) [8] have used three different types of time–frequency wavelet representation (Morse, Gabor, and the Bump mother wavelet) and deep learning models to classify forearm flexion and extension. From the recent literature, the authors have identified that the two-dimensional (time–frequency) representation significantly helps in improving the models' overall performance.

Fractional calculus is a branch of mathematics enabling the differentiation or integration of functions into fractional orders, providing a concise representation of a system. The incorporation of fractional orders has proven highly efficient in addressing intricate problems [9]. In recent years, researchers have integrated fractional calculus into swarm intelligence algorithms to enhance the classification of electrophysiological signals [9, 10]. In this study, fractional order bat optimization is employed to enhance the performance of CNN. Banharnsakun (2019) [11] has developed a CNN model with distributed ant bee colony optimization to improve the accuracy and computational time. The author has concluded that the developed CNN framework has demonstrated improvement in overall effectiveness pertaining to computational time and accuracy. Singh et al. (2021) [12] have proposed multilevel particle swarm optimization for tuning the hyperparameters and architecture of CNN. The authors signified that the proposed technique automatically tunes the hyperparameters for the CNN architecture. Chen et al. (2022) [13] have devoted intelligent optimization through fractional order CNN with population extremal optimization to improve the performance of CNN architecture.

Fractional order systems combined with evolutionary features provide a robust framework for system identification and parameter estimation. Unlike traditional optimization methods, evolutionary algorithms explore complex parameter spaces, making them effective in scenarios involving nonlinearity, high dimensionality, or intricate parameter interactions. This synergy enhances the efficiency and accuracy of the optimization process, enabling the discovery of optimal solutions. Considering these factors, the primary objective of this research work concentrates in building a model with ingenuity by extending CNN incorporated with fractional order bat optimization in predicting typical and atypical EMG signals.

The advent of SP-WVT emerges as an asset for time–frequency analysis across a spectrum of applications. It also provides substantial benefits, including enhanced time–frequency resolution, increased resilience to noise, and improved interpretability when contrasted with the conventional Wigner–Ville Transform. Consequently, in this work, SP-WVT is used for transformation of acquired raw EMG signals which is applied for training the developed CNN. In addition, the performance results of the developed fractional order bat optimized CNN were compared with the performance of bat optimized CNN.

2 Methodology

2.1 Data collection

The work focuses on selecting the bicep brachii muscle region at low-level concentric needle electrode insertion to obtain EMG signals related to myopathy, ALS, and normal conditions. The EMG signals were collected under usual conditions for action potential analysis. The high- and low-pass filters of the EMG amplifier were set at 2 Hz and 10 kHz. A total of 150 pre-processed signals were examined at the age group of 19–67 years with inclusion of male and female individuals' group, comprising 50 signals each from individuals with myopathy, ALS, and those considered normal. These signals, sourced from the EMGLAB database accessed in July 2017, had a duration of 11.8 s each, with a sampling frequency of 23437.5 Hz [14]. Figure 1a–c showcases typical EMG signals for myopathy, normal, and ALS. These signals typically exhibit non-stationary characteristics, making it challenging to discern between normal and abnormal patterns through visual inspection alone.

2.2 Smoothed pseudo-Wigner–Ville transform (SP-WVT)

The Wigner–Ville transform and its different variations have gained significant popularity in numerous fields for analysing non-stationary signals in terms of time–frequency. A primary issue associated with the Wigner–Ville

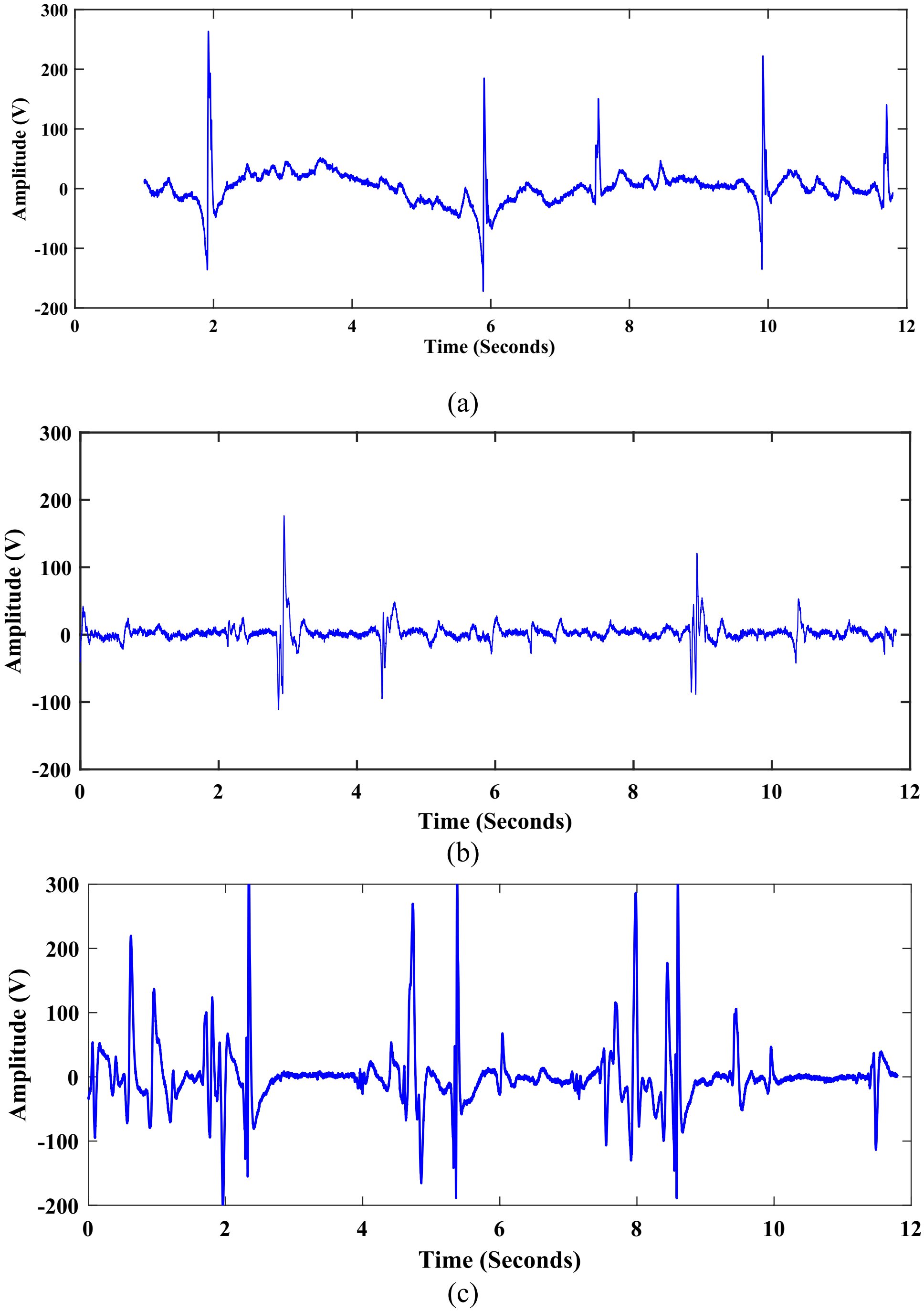


Fig. 1 **a**–**c** Typical EMG signals for **a** normal, **b** myopathy, and **c** ALS, representing a period of 11.8 s

transform is the production of undesirable components, referred to as cross terms, which can hinder the clear understanding of the proper distribution function [15]. The amplitude of these cross-terms can be considerably higher than the amplitudes of the actual distribution function. Hence, the SP-WVT suppresses this cross-term and provides the instantaneous time–frequency coefficients for a signal [16]. The SP-WVT employs two window operations, k and h, which serve the purpose of SP-WVT in the time and frequency domains, respectively. The mathematical expression for SP-WVT is as follows [15, 16]:

$$\text{Smoothed Pseudo WVT}(t, v) = \int_{-\infty}^{\infty} k(\tau) \int_{-\infty}^{\infty} h(g - t) z(g + \frac{\tau}{2}) z * (g - \frac{\tau}{2}) e^{-j2\pi v\tau} dg d\tau \quad (1)$$

where $k(t)$ and $h(t)$ represent the time and frequency representation, *signifies the complex conjugate. The SP-WVT improves cross-case suppression while allowing independent control over temporal and frequency resolutions. Also, it offers flexibility in selecting different window functions for both the time and frequency domains [15]. The SP-WVT reconstruction technique is applied in this study to transform time–frequency images from EMG signals.

2.3 Fractional bat optimization algorithm

The bat algorithm, invented by Yang (2010) [17], is a nature-inspired intelligence algorithm that draws ideas from the foraging behaviour of bats. The algorithm is specifically designed to tackle complex nonlinear problems. Bats emit signals within a frequency range of 20 kHz–500 kHz. The algorithm begins with an initial population of bats, which uses an echolocation method to update their positions iteratively. The summarized fundamental rules of the bat algorithm [18] are as follows:

- Bats depend on their echolocation skills to gauge distances and differentiate between prey and obstacles.
- Each bat takes flight in a random direction when searching for prey, equipped with attributes such as position, velocity, frequency, wavelength, and loudness. As the bat approaches its target, it autonomously adjusts the frequency of its pulse emission rate and the range of its loudness.
- The pulse emission rate, frequency, and loudness vary during the search.

Through the utilization of these fundamental principles in the bat algorithm, the velocity and position within each search space are updated. As a result, Eqs. (2–4) [18] provide the updating equations for the velocity $V(t)$ and position $X(t)$.

$$\mathrm{freq}_i = \mathrm{freq}_{\min} + (\mathrm{freq}_{\max} - \mathrm{freq}_{\min})\beta \tag{2}$$

$$v_i(t+1) = v_i(t) + (x_i(t) - x*)\mathrm{freq}_i \tag{3}$$

$$x_i(t+1) = x_i(t) + v_i(t) \tag{4}$$

Here, β represents a random value following a uniform distribution between 0 and 1, while x^* denotes the global best position within the bat's search space [18]. In this work, fractional calculus integrated with bat optimization techniques to select the relevant features for the classification of EMG signals.

The fractional derivatives, expressed using finite sets, are described by Eq. (5), known as the Grunwald–Letnikov method [19].

$$D^\alpha[x(t)] = \lim_{k\to 0}\left[\frac{1}{k^\alpha}\sum_{h=0}^{+\infty}\frac{(-1)^h\Gamma(\alpha+1)x(t-hk)}{\Gamma(h+1)\Gamma(\alpha-h+1)}\right] \tag{5}$$

To convert non-integer order derivative into a discrete time series format, Eq. (5) is modified by incorporating the sampling time (T) and truncation value (r). The resulting modified equation (6) is then expressed as [19].

$$D^\alpha[x(t)] = \frac{1}{T^\alpha}\sum_{h=0}^{r}\frac{(-1)^h\Gamma(\alpha+1)x(t-hT)}{\Gamma(h+1)\Gamma(\alpha-h+1)} \tag{6}$$

Bat optimization ensures convergence by iteratively updating the velocity and position in each search iteration. However, the bat optimization algorithm is enhanced by incorporating fractional calculus to achieve a faster convergence rate. Furthermore, Eq. (3) of the bat optimization is reformulated by setting the order to $\alpha = 1$, resulting in the following expression:

$$v_i(t+1) - v_i(t) = (x_i(t) - x*)\mathrm{freq}_i \tag{7}$$

The derivative form of Eq. (7) is rewritten as,

$$D^\alpha[v_i(t+1)] = (x_i(t) - x*)\mathrm{freq}_i, \qquad 0 \le \alpha \le 1 \tag{8}$$

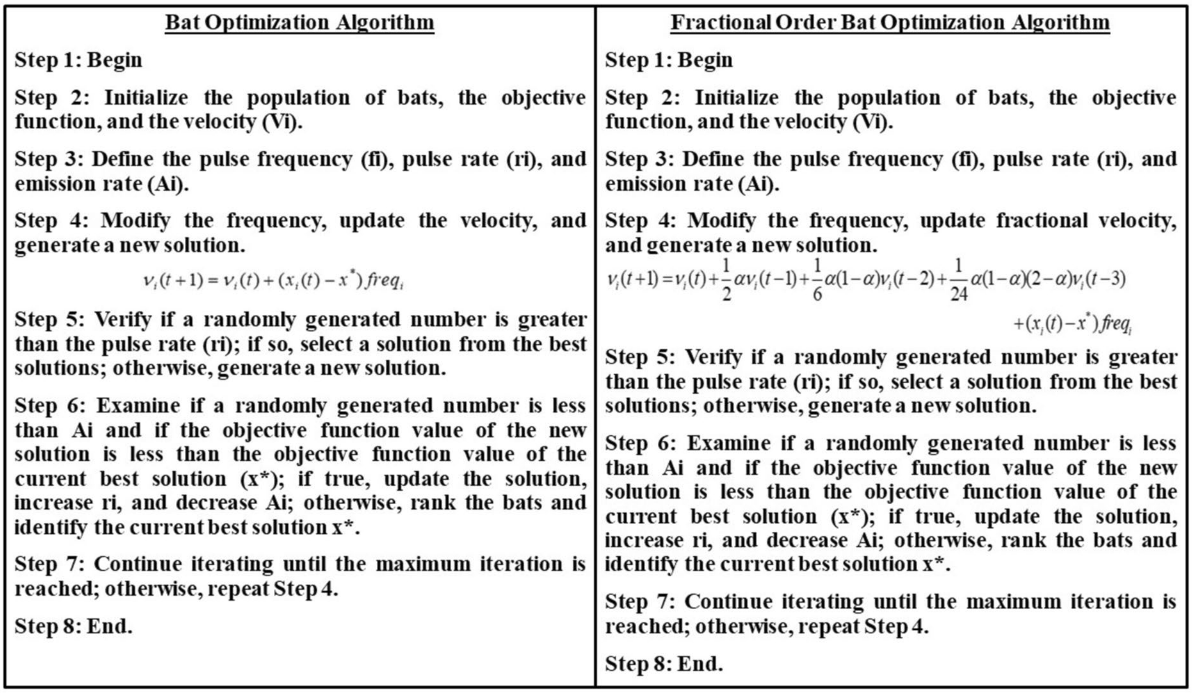
where $D^\alpha[V_i(t+1)]$ is the derivative form of $V_i(t+1)$ with respect to fractional order α. The derivative form of Eq. (8) with $r = 4$ is expressed as [19],

$$\begin{aligned} &v_i(t+1) - v_i(t) - \frac{1}{2}\alpha v_i(t-1) - \frac{1}{6}\alpha(1-\alpha)v_i(t-2) \\ &- \frac{1}{24}\alpha(1-\alpha)(2-\alpha)v_i(t-3) \end{aligned} \tag{9}$$

or

$$\begin{aligned} v_i(t+1) =& v_i(t) + \frac{1}{2}\alpha v_i(t-1) + \frac{1}{6}\alpha(1-\alpha)v_i(t-2) \\ &+ \frac{1}{24}\alpha(1-\alpha)(2-\alpha)v_i(t-3) \end{aligned} \tag{10}$$

Figure 2 illustrates the algorithms for bat optimization and fractional order bat optimization. In this study, both bat optimization and fractional order optimization methods are applied in conjunction with a deep learning model to classify normal and abnormal EMG signals. The bat search space is determined based on optimal convergence rate which depends on the optimization parameter namely pulse frequency, pulse emission rate, and loudness. To find the best convergence rate in bat and fractional bat optimization algorithm, the optimization parameters are selected by varying different parameters (pulse emission rate [0 2], loudness [0 1], pulse frequency [0 100], and fractional order [0 1]) with respect to the iteration number. The training parameters used for fractional bat optimization based on the best convergence rate are listed in Table 1.



Bat Optimization Algorithm

Step 1: Begin

Step 2: Initialize the population of bats, the objective function, and the velocity (Vi).

Step 3: Define the pulse frequency (fi), pulse rate (ri), and emission rate (Ai).

Step 4: Modify the frequency, update the velocity, and generate a new solution.

$$v_i(t+1) = v_i(t) + (x_i(t) - x^*)\,freq_i$$

Step 5: Verify if a randomly generated number is greater than the pulse rate (ri); if so, select a solution from the best solutions; otherwise, generate a new solution.

Step 6: Examine if a randomly generated number is less than Ai and if the objective function value of the new solution is less than the objective function value of the current best solution (x*); if true, update the solution, increase ri, and decrease Ai; otherwise, rank the bats and identify the current best solution x*.

Step 7: Continue iterating until the maximum iteration is reached; otherwise, repeat Step 4.

Step 8: End.

Fractional Order Bat Optimization Algorithm

Step 1: Begin

Step 2: Initialize the population of bats, the objective function, and the velocity (Vi).

Step 3: Define the pulse frequency (fi), pulse rate (ri), and emission rate (Ai).

Step 4: Modify the frequency, update fractional velocity, and generate a new solution.

$$v_i(t+1) = v_i(t) + \frac{1}{2}\alpha v_i(t-1) + \frac{1}{6}\alpha(1-\alpha)v_i(t-2) + \frac{1}{24}\alpha(1-\alpha)(2-\alpha)v_i(t-3) + (x_i(t) - x^*)\,freq_i$$

Step 5: Verify if a randomly generated number is greater than the pulse rate (ri); if so, select a solution from the best solutions; otherwise, generate a new solution.

Step 6: Examine if a randomly generated number is less than Ai and if the objective function value of the new solution is less than the objective function value of the current best solution (x*); if true, update the solution, increase ri, and decrease Ai; otherwise, rank the bats and identify the current best solution x*.

Step 7: Continue iterating until the maximum iteration is reached; otherwise, repeat Step 4.

Step 8: End.

Fig. 2 Algorithm of bat and fractional order bat optimization algorithm

Table 1 Training parameters for fractional bat optimization

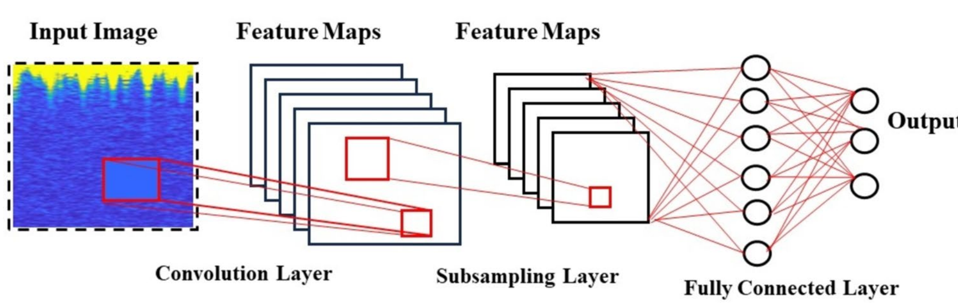
Training parameters	Specification
Pulse frequency	[0 35]
Maximum iteration	100
Pulse emission rate	1.3
Loudness	0.3
Fractional order	0.9

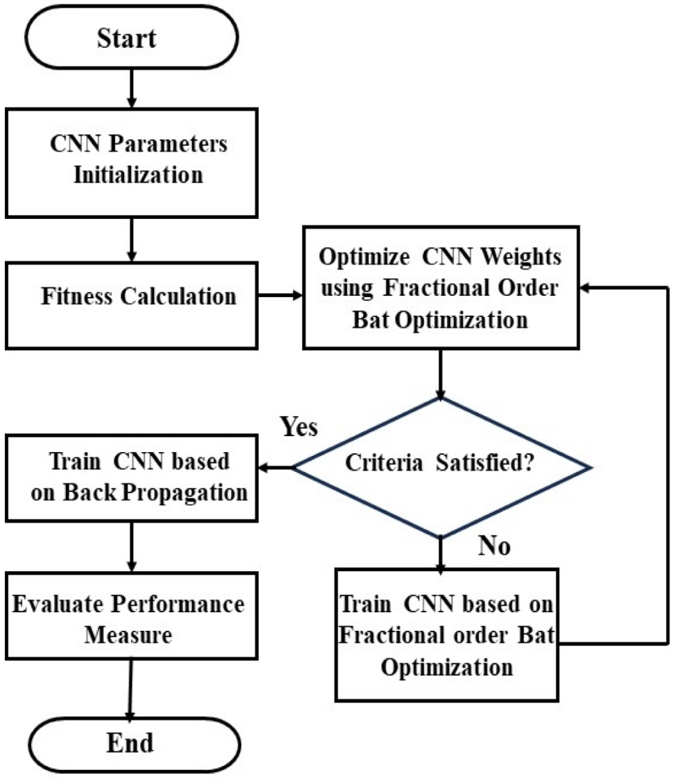
2.4 Convolutional neural network (CNN)

A CNN is a type of artificial neural network that operates feed-forwardly and possesses a unique structure. A conventional CNN consists of minimum one or more convolutional layers, average pooling layers, and a fully connected layer which is depicted in Fig. 3. The superficial convolutional layer receives an input in the form of an image with dimensions $H \times W \times C$ (H, W, and C symbolizes the height, width, and the number of channels). Traditionally, convolutional layer comprises N filters, each of size $s \times s \times l$ (s is smaller than H, and l is equal to C). The utilization of filters of specific dimensions leads to the creation of a locally connected structure. Within this structure; every filter interacts with the image through convolution, generating k feature maps. Following the generation of feature maps, each map undergoes sub-sampling, over $p_i \times p_i$ adjacent regions. The sub-sampling layer works on each feature map individually and adjusts its spatial size [20, 21].

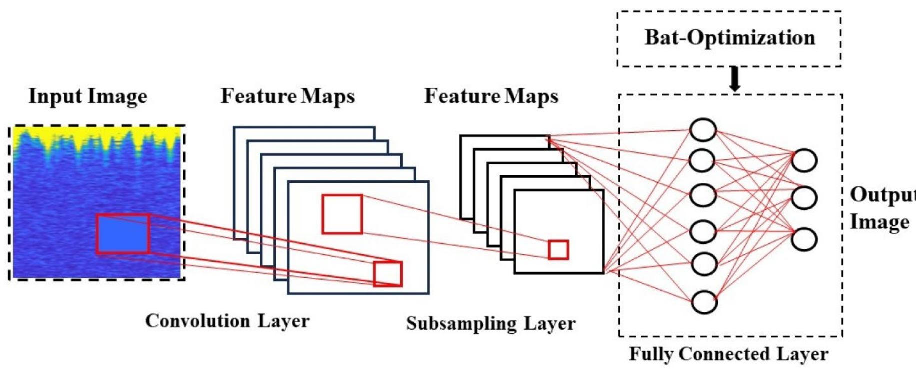
Subsequently, an activation function and bias are administered to every feature map. A variable number of fully connected layers can be present following the convolutional layers. These fully connected layers leverage the

Fig. 3 A typical CNN architecture

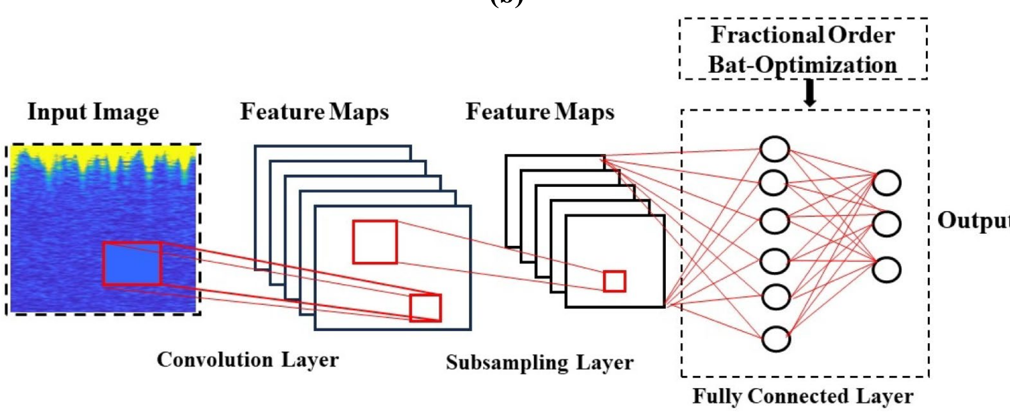




(a)



(b)



(c)

Fig. 4 **a** Flowchart of fractional order bat-CNN, **b** architecture of bat-CNN **c** architecture of fractional order bat-CNN

Table 2 Training parameters of CNN with fractional order bat optimization algorithms

Training parameters	Specification
Maximum epochs	45
Minibatch size	128
Shuffle	Every-epoch
Initial learning rate	1.00e-03
Validation frequency	8
Momentum	0.900
Verbose and verbose frequency	1, 50
*L*2-regularization	0.0001
Gradient threshold method	I2norm

extracted features to classify the input image into different categories, utilizing the training dataset [20].

The general training procedure of a conventional CNN is described as follows [20]:

Step 1: Initial random values are chosen for filters and weights.

Step2: Input the training image dataset into the input layer of the network; further, it is forwarded to the other layers of the network including convolution, down-sampling operations, fully connected layer, and output layer for determination of results.

Step 3: Overall error of the output layer is estimated using equation (11),

$$\text{Overall Error} = \sum(\textit{Target probability} - \text{Actual}\,\textit{Probability}) \tag{11}$$

Step 4: Backpropagation is utilized to compute the error gradients using network weights; further, the network updates weights and bias using gradient descent which subsequently minimizes the overall error.

Step 5: Iterate through each image in the training input set, performing steps 2–4 repeatedly.

2.5 Fractional order bat optimization CNN

Network performance can be trapped by an issue of local optima during the training phase of a neural network using a gradient descent algorithm. Additionally, the initial weights assigned for a trained neural network classifier play a significant role in determining its effectiveness [11, 13]. This study uses the fractional order bat optimization algorithm to choose the optimal set of weights from varied initial weight configurations. Precisely, Eq. (11) chooses the weight set with minimal error. Equation (11) also serves as the fitness function within the fractional order bat optimization algorithm. To achieve the optimal weights, multiple trials were conducted using different initial weights [11, 13]. Figure 4a–c illustrates the fractional order bat-CNN algorithm.

Initially, the CNN is trained and generates a solution, and the fitness of the initial solution is evaluated using the classification error of the CNN classifier, indicating its effectiveness. The initial solution is considered as the initial bat position for fractional order bat-CNN. The bat's position is updated, and share newly discovered solutions within the search space, select the solutions with higher fitness, update those solutions, and re-evaluate their fitness [13]. The training parameters used for the fractional order bat optimization CNN algorithms are listed in Table 2. For training the fractional order bat-CNN, 80% of data set were used and 20% of data set were used for testing and tenfold cross-validation is employed.

The study utilizes various performance metrics, including accuracy, sensitivity, specificity, precision, false positive rate, $F1$ score, Matthew correlation coefficient, and Kappa. These metrics are derived from confusion matrices, which involve true positive, true negative, false positive, and false negative components, with their calculation formula provided in Eqs. (12–19)

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Total Population}(P + N)} \tag{12}$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{13}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{14}$$

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}} \tag{15}$$

$$\text{False Positive Rate (FPR)} = \frac{\text{False Positive}}{\text{True Negative} + \text{False Positive}} \tag{16}$$

$$F1\text{Score} = \frac{2 \times \text{True Positive}}{2 \times \text{True Positive} + \text{False Positive} + \text{False Negative}} \tag{17}$$

$$\text{MCC} = \frac{\text{True Positive} \times \text{True Negative} - \text{False Negative} \times \text{False Positive}}{(\text{True positive} + \text{False positive}) \times (\text{False Positive} + \text{True Negative}) \times (\text{True Positive} + \text{False Negative}) \times (\text{False Negative} + \text{True Negative})} \tag{18}$$

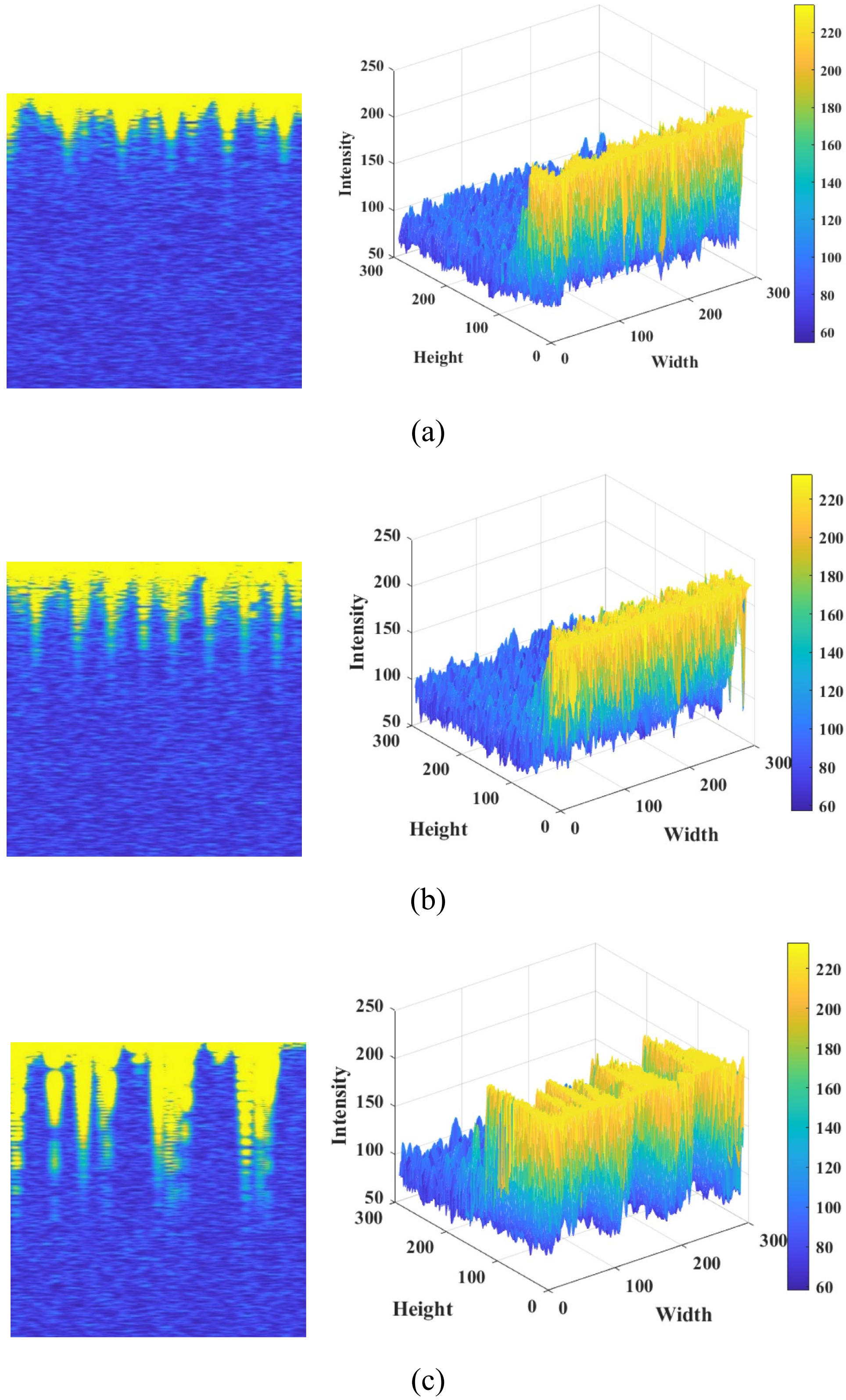


Fig. 5 Mesh plot of SP-WVT time–frequency images: **a** Normal biceps brachii muscle signal, **b** myopathy biceps brachii muscle signal, and **c** ALS biceps brachii muscle signal

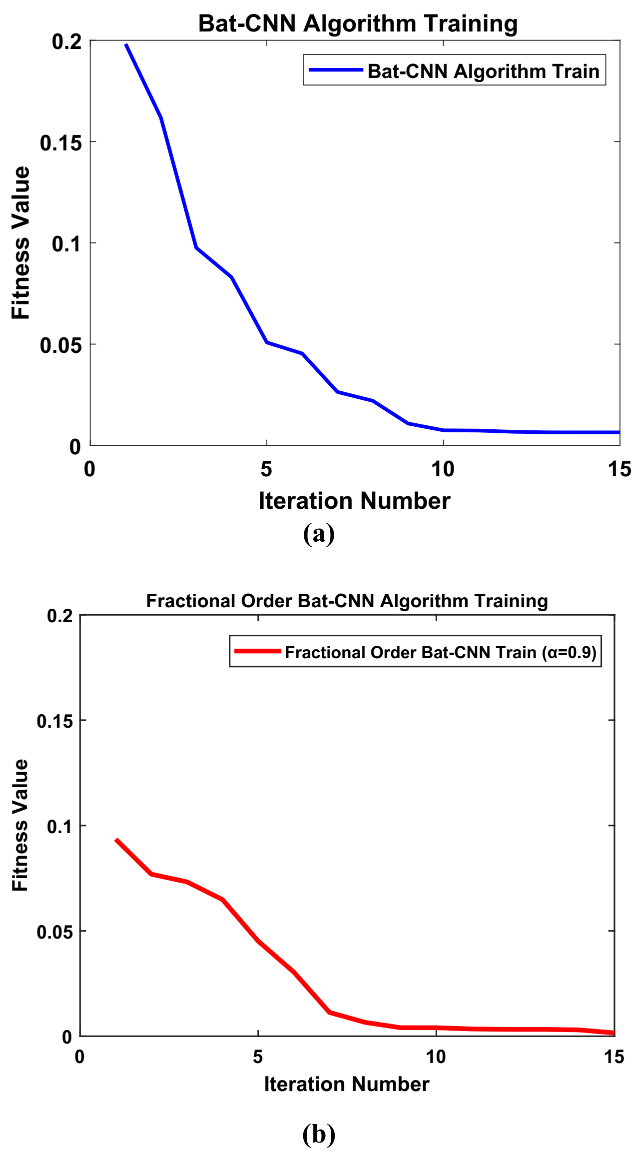


Fig. 6 Fitness value vs iteration: **a** Bat-CNN and **b** fractional bat-CNN

$$\text{Kappa} = \frac{2 \times \text{True Positive}}{2 \times \text{True Positive} + \text{False Negative} + \text{False Positive}} \quad (19)$$

3 Results and discussion

The empirical results of fractional order bat-CNN for the differentiation of typical and atypical EMG signals are discussed in this section. Fractional order bat-CNN was implemented and executed in MATLAB 2023a licensed version. The 2-D reconstructed representation contains more information than 1-D representation which includes temporal dynamics, analysis of specific frequency components associated with different muscle activities, including low-frequency fatigue, high-frequency oscillations, and spectral changes during dynamic tasks. 2-D representation also assists in detecting and evaluating transient occurrences, bursts of muscular activity, or frequency-specific phenomena, enhancing the ability to derive significant insights from the EMG signal. Figure 5a–c shows the mesh plot of time–frequency image reconstruction using a SP-WVT of normal and abnormal EMG signals. It has been noted that abnormal EMG signals exhibit a higher intensity distribution compared to normal EMG signals.

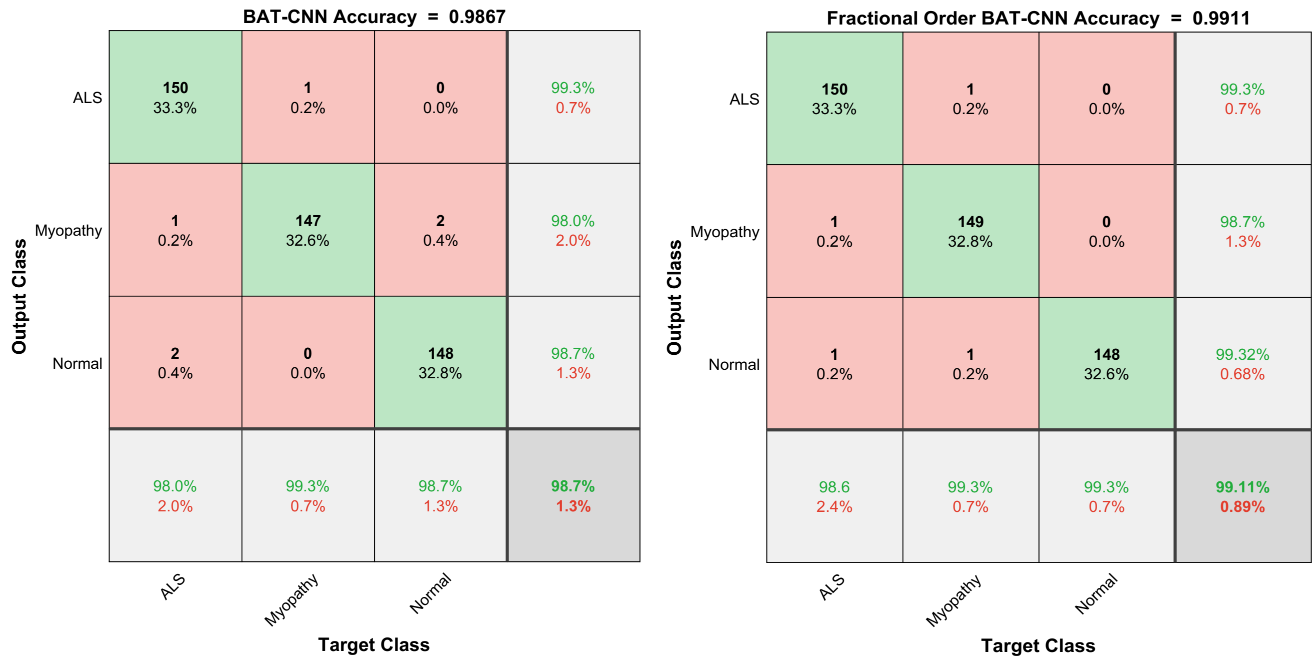
In order to find the convergence, the fractional order bat optimization CNN and bat-CNN were executed by varying the number of iterations. Each optimization algorithm was carried out with 15 maximum iterations, a bat size of 20, a dimension size of 30, and optimization parameters (pulse emission rate ($A0 = 1.3$), loudness ($r0 = 0.3$), and pulse frequency (0, 35)). Figure 6a–b illustrates the convergence curve obtained for the algorithms.

The convergence curve clearly indicates that the fractional order bat-CNN algorithm with $\alpha = 0.9$ achieves faster convergence compared to the bat-CNN algorithm for the given optimization parameters.

The fractional order bat-CNN is modelled for classification of transformed normal bicep brachii muscle and abnormal bicep brachii muscle images. The fractional order bat-CNN is trained with an image size of $64 \times 64 \times 1$, which is connected to subsequent layers with kernel filter size 3×3 to enhance learning. Further, relu activation functions, population-based batch normalization, and max pooling with a pool size of 4×4 are applied. Subsequently, fractional order bat optimization is integrated with fully connected layer for updating the weights, followed by softmax layer, and classification layer for the EMG signal classification. The developed model utilizes cross-entropy as the loss function. The confusion matrix for maximum accuracy exhibited by the bat-CNN and fractional order bat-CNN is presented in Fig. 7a, b.

Table 3 depicts the overall performance measures of fractional order bat-CNN and bat-CNN optimization algorithm for the classification of transformed normal bicep brachii muscle, myopathy bicep brachii muscle, and ALS bicep brachii muscle images. It is identified that the fractional bat-CNN attains higher accuracy (99.11%) when compared to the accuracy of bat-CNN (98.67%).

The accuracy and loss of the fractional order bat-CNN for both the training and validation sets are plotted as a function of iteration in Fig. 8a, b. It is noted that the accuracy of the training and validation sets of the fractional order bat-CNN significantly improves after the fifth iteration.



(a) (b)

Fig. 7 Confusion matrix: **a** Bat-CNN and **b** fractional order bat-CNN

From the results obtained, it is obvious that the fractional order bat-CNN is more efficient for predicting normal and abnormal EMG signals. The results reveal that the increase in accuracy observed after the fifth iteration in both the training and validation sets of the fractional order bat-CNN can be attributed to a variety of factors. These factors include model convergence, enhanced feature learning, regularization techniques, data augmentation methods, and fine-tuning of hyperparameters. Together, these elements contribute to the continuous improvement of the model performance throughout the training process. The result also uncovers the importance of fractional order integrated with modelled bat optimization CNN in improving the performance. Although the fractional order bat-CNN has shown improved performance, there is a noticeable rise in computational cost for the bat-CNN model.

Table 3 Overall performance measures of fractional order bat-CNN and bat-CNN

Performance measure	Fractional order bat-CNN	Bat-CNN
Accuracy	99.11%	98.67%
Recall	99.11%	98.67%
Specificity	99.56%	99.33%
Precision	99.12%	98.68%
*F*1 score	99.11%	98.67%
Matthew correlation coefficient	98.67%	98.01%
Kappa	98.00%	97.01%

4 Conclusion

EMG, which involves the galvanizing activity of nerves and muscles, serves as a valuable diagnostic tool for identifying muscle and nerve disorders. The ability to differentiate between normal and abnormal EMG signals, including myopathy and ALS, is pivotal for supporting computerized diagnostic tools. This is especially important because EMG signals are non-stationary. Consequently, it is essential to develop an efficient classification system for EMG signals to enable computer-assisted identification of abnormalities. The time series of EMG signals are initially reconstructed into time–frequency images using the smoothed pseudo-Wigner–Ville transform. Subsequently, the convolution neural network (CNN) performance is enhanced by introducing the fractional order bat optimization algorithm, enabling the classification of EMG signals. The performance of the fractional bat-CNN is compared to that of the bat-CNN. The results demonstrate the highly effective nature of the fractional bat-CNN in accurately classifying normal and abnormal EMG images, achieving an impressive accuracy rate of 99.11%.

Furthermore, the fractional order bat-CNN approach demonstrates enhanced performance in comparison to the bat-CNN method. The results also underscore the importance of integrating fractional order with CNN-modelled bat optimization to improve the performance.

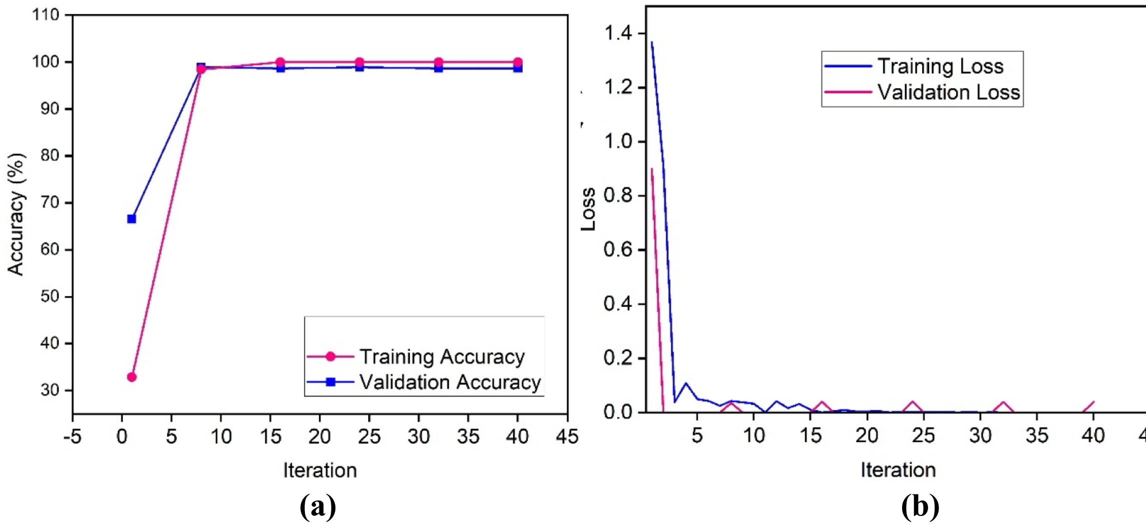


Fig. 8 **a** Accuracy and **b** loss of fractional order bat-CNN

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