Abstract

Electroencephalogram (EEG) is the key component in the field of analyzing brain activity and behavior. EEG signals are affected by artifacts in the recorded electrical activity; thereby it affects the analysis of EEG. To extract the clean data from EEG signals and to improve the efficiency of detection during encephalogram recordings, a developed model is required. Although various methods have been proposed for the artifacts removal process, still the research on this process continues. Even if, several types of artifacts from both the subject and equipment interferences are highly contaminated the EEG signals, the most common and important type of interferences is known as Ocular artifacts. Many applications like Brain-Computer Interface (BCI) need online and real-time processing of EEG signals. Hence, it is best if the removal of artifacts is performed in an online fashion. The main intention of this proposal is to accomplish the new deep learning-based ocular artifacts detection and prevention model. In the detection phase, the 5-level Discrete Wavelet Transform (DWT), and Pisarenko harmonic decomposition are used for decomposing the signals. Then, the Principle Component Analysis (PCA) and Independent Component Analysis (ICA) are adopted as the techniques for extracting the features. With the collected features, the development of optimized Deformable Convolutional Networks (DCN) is used for the detection of ocular artifacts from the input EEG signal. Here, the optimized DCN is developed by optimizing or tuning some significant parameters by Distance Sorted-Electric Fish Optimization (DS-EFO). If the artifacts are detected, the mitigation process is performed by applying the Empirical Mean Curve Decomposition (EMCD), and then, the optimized DCN is used for denoising the signals. Finally, the clean signal is generated by applying inverse EMCD. Based on the EEG data collected from diverse subjects, the proposed method has achieved a higher
performance than that of conventional methods, which demonstrates a better ocular-artifact reduction by the proposed method.

**Keywords**  Electroencephalogram · Ocular artifacts · 5-level discrete wavelet transform · Pisarenko harmonic decomposition · Optimized deformable convolutional networks · Empirical mean curve decomposition · Distance sorted-electric fish optimization

1 Introduction

The evaluation of electrical activities inside a brain is carried out by EEG using the electrodes attached to the scalp. This process is known as a non-invasive brain imaging technique [46]. The advantages of using EEG signals in the medical field are fast functionality, safe to use, relatively inexpensive, simple to operate, and portability. On the other hand, several artifacts of technical and biological origins highly contaminate the EEG signals [3, 4]. The most common types of artifacts are arising from muscle activities, heartbeat, eye blink, or movements. These artifacts are considered a major hindrance in the analysis of EEG signals. The human eyes produce large electric potential during eye blinks, and the resulting signal is known as Electrooculogram (EOG). The EOG signal spreads all over the scalp, which contaminates the EEG signals that are known as ocular artifacts [10, 16]. These ocular artifacts interfere while measuring the brain signals and produce significant changes in measurements, which may induce negative waveforms with high amplitude. Therefore, the recognition and removal of ocular artifacts from EEG signals is an essential process. Various techniques are available for the removal of ocular artifacts from EEG signals [11].

In the past research works, Singular Value Decomposition (SVD) and PCA have been used to remove ocular artifacts. Although both methods have been used for recognizing the artifacts, they have not removed them completely due to some wrong assumptions while measuring the EEG signals. Adaptive filtering is another technique that has been used for the removal of ocular artifacts. It also has some restrictions in results due to ignorance of some information among electrodes [35, 38]. ICA is a technique that has been used for analyzing and then eliminating the ocular artifacts from EEG signals. This technique includes linear transformation, which optimizes the statistical dependence among the independent components (ICs) since the ICs lost the data in EEG signals [37, 39]. However, the ICA is not trained well for removing the ocular artifacts completely. The blind Source Separation (BSS) algorithm has been used to separate the EOG and EEG into ICs statistically. The separation process was done again on EEGs with inverted EOG channels. However, it has some restrictions on reference EOG channels [15].

Adaptive Noise Cancellation (ANC) and DWT techniques are used to remove ocular artifacts from EEG signals [8]. This method can perform using a single EEG signal without the need for an EOG signal. Although this model has given reasonable results with superior performance, it has dependent on wavelet form and threshold function, which leads to loss of data in EEG signals [12, 20]. The existing models have a lot of challenges to overcome. Thus, deep learning is used to solve the issues in conventional methods. It also provides various techniques, which efficiently remove ocular artifacts from the EEG signals. The followings are the advantages of using deep learning methods: (a) strong generalization ability, (b) time-saving, (c) non-use of additional EOG reference signals, etc. Most of the deep learning models provide high clearance in the process of recognizing and mitigating the ocular artifacts from EEG signals [14, 41]. This paper proposed a novel 1-D Electroencephalogram (EEG) signal denoising network with a 2-D transformer, namely EEGDnet.
By fusing non-local self-similarity in self-attention blocks and local self-similarity in feed forward blocks, the negative impact caused by noises and outliers can be reduced significantly. The existing reviews mainly focus on the applications of CNN in different scenarios without considering CNN from a general perspective. This review aims to provide novel ideas and prospects in this fast-growing field. Motivated by this consideration, the contribution of this paper is to investigate the deep learning approaches applied to healthcare systems by reviewing the cutting-edge network architectures, applications, and industrial trends. This paper proposed a flexible hydrogel biosensor made of conductive HPC/PVA (Hydroxypropyl cellulose/Polyvinyl alcohol) hydrogel and flexible PDMS (Polydimethylsiloxane) substrate. The proposed biosensor is affixed to the wheelchair user’s forehead to collect Electrooculogram (EOG) and strain signals, which are the basis to recognize eye movements. This paper presented a novel technique to detect randomly generated domain names and domain name system (DNS) homograph attacks without the need for any reverse engineering or using nonexistent domain (NXDomain) inspection using deep learning. The challenges for the existing PSO are listed below, data loss, high sensitivity, time constraints, and low accuracy. GWO does not solve complex numerical optimization problems. The convergence speed of the GWO algorithm is typically slower than those of the representative population-based algorithms. It can also easily get trapped in the local optima when solving complex multimodal problems. EFO is not suitable for online analysis of EOG and EEG correlation and also it shows weak performance when compared with the other algorithms. Therefore, to overcome these challenges in this research work, a new DS-EFO algorithm is developed for detection and mitigation model of ocular artifacts from EEG signals for attaining the minimum error rate value and also increases the accuracy when compared with the other conventional heuristic algorithm and classifiers. The main contribution of the proposed model of detection and removal of ocular artifacts from EEG signals is given here:

- To propose a new detection and mitigation model of ocular artifacts from EEG signals by various techniques like 5-level DWT and Pisarenko harmonic methods for decomposition of signals, PCA and ICA for features extraction from signals, EMCD for decomposition of signals and optimized DCN with DS-EFO for detection of ocular artifacts with enhanced accuracy rate.
- To establish an effective prevention model of ocular artifacts with a help of developed optimized DCN by the proposed DS-EFO for minimizing MAE for attaining an efficient removal of ocular artifacts.
- The novelty of the research work is, developing a new DS-EFO algorithm for detection and prevention techniques. The parameters of DCN such as epoch and learning rate are optimized by the DS-EFO algorithm to improve the efficiency of the proposed model in terms of detection and prevention.
- To validate the efficiency of detection and prevention phases of ocular artifacts model by estimating with trained data sets from BCI applications by various performance metrics through comparing with the existing algorithms.

The remaining sections of this paper are given here. Section II discusses the existing methodologies, their advantages, and their challenges. Section III presents deep learning-based detection and prevention of ocular artifacts from EEG signals. Section IV briefly reviews the ocular artifacts’ detection by optimized DCN. Section V elaborates on the prevention of ocular artifacts by EMCD and optimized DCN. Section VI analyzes the performance of the detection and prevention model of ocular artifacts from EEG signals. Section VII concludes the proposed detection and mitigation model of ocular artifacts using EEG signals.
2 Literature survey

2.1 Related works

In 2018, Sai et al. [27] have proposed a new model using a Support Vector Machine (SVM) with wavelet-ICA. The ICA has separated the components of the signal to identify the artifacts. The developed model has efficiently identified and removed the artifacts from EEG signals using a fully automatic extendable system without depending on any thresholding function. The analysis of test data using contaminated eye blink artifacts has shown that the proposed method has provided better performance in the identification of artifacts than the existing methods in terms of thresholding function.

In 2009, Mosquera et al. [17] have proposed a method based on ICA and Recursive Least Squares (RLS) for removing eye movement artifacts. The proposed algorithm has used combination methods of ICA and adaptive filtering cancellation methods. The EOG and EEG signals were first separated into ICs using the ICA method. Then, the method has used a reference signal, which was extracted from the measurements of horizontal and vertical eye movements. The input reference signal was initially projected to the ICA phase and then the RLS algorithm has evaluated the interference of artifacts.

In 2013, Betta et al. [1] have developed a novel method for removing ocular artifacts, which was an automated system to analyze Rapid Eye Movement (REM) signals. This method has used both the detection algorithm and removal system, in which the detection algorithm has included the correlation of DWT and adaptive filtering techniques to improve the performance of the artifacts removal system with better accuracy.

In 2015, Selvan et al. [30] have proposed an efficient technique for the removal process of artifacts from EEG signals. This model has combined two adaptive filtering techniques. The first one was ANC, which was used to remove the noise signal from the primary signal and reference signal. Secondly, adaptive signal enhancement has been used to enhance the output signal from the ANC. This technique has provided a fast convergence rate without using more nodes.

In 2015, Peng et al. [19] have presented a new model to remove ocular artifacts from EEG signals, which was based on DWT and ANC. The DWT waveforms were used to construct reference signals of ocular artifacts with the lowest coefficient values of the EEG signals corresponding to the frequency. The accuracy of the proposed model was compared with the existing model in terms of simulated and measured data.

In 2005, Shoker et al. [34] have proposed a method with a combination of two algorithms namely SVM and BSS. This method has removed artifacts based on selected statistical features of ICs extracted from the EEG signals. In BSS, the EOG signals were separated from EEG signals as independent sources by using Second-Order Blind Identification (SOBI) algorithm. The artifacts were identified and removed from the ICs by using the SVM algorithm. Further, the remaining ICs were reanalyzed to provide EEG signals without any artifacts.

In 2017, QuaziS et al. [22] have implemented an algorithm for removing artifacts from EEG signals, which was based on a hybrid scheme namely Firefly-Levenberg-Marquardt (FLM) algorithm. The FLM algorithm has used with an adaptive filter, in which the EEG signals were applied as an input signal. Then, the proposed model has reduced the artifacts from the filtering signal. The performance evaluation of the proposed model was conducted based on three factors namely mean square error, Signal-to-Noise Ratio (SNR), and computational time.

In 2017, Jafarifarmand et al. [5] have developed a model with the combination of two approaches namely ICA and ANC. The ICA technique has been used to extract the source signals...
of artifacts as independent components. The extracted results have been used in the ANC technique based on neural networks. This model could not need any additional electrodes to perform in a single EEG channel and also has less computational time. The proposed model was analyzed using BCI recorded data to achieve reliable results in both online and offline phases.

In 2021, Ravi et al. [24] have proposed large-scale learning with stacked ensemble meta-classifier and deep learning-based feature fusion approach for COVID-19 classification. The features from the penultimate layer (global average pooling) of EfficientNet-based pre-trained models were extracted and the dimensionality of the extracted features was reduced using kernel Principal Component Analysis (PCA). Then the feature fusion approach was employed to merge the features of various extracted features.

In 2021, Ravi et al. [25] have presented a detailed investigation and analysis of 26 pretrained Convolutional Neural Network (CNN) models using a recently released and large public database of TB X-rays. The proposed models can classify the X-ray of a patient as TB, Healthy, or Sick but non-TB. Various visualization methods were adopted to show the optimal features learned by the pre-trained CNN models.

2.2 Problem statement

In the medical diagnosis field, the EEG signals are used for brain electrical activity recordings. The EEG signals are often contaminated with different types of artifacts, and among them, ocular artifacts are considered as a major source of the noise. The identification and removal of ocular artifacts from EEG signals are considered as a main challenging task. Numerous traditional detection and mitigation techniques are reviewed in Table 1. SVM [27] has improved efficiency in the identification of artifacts and offers better artifact removal without much degrading the time and frequency resolution of the signal. However, this model needs a large number of features for training data sets when dealing with large datasets with more noise. RLS-ICA [17] provides a fast convergence rate and improves performance in artifacts removal and independent noise removal, without calibration. However, this method is not suitable for online analysis of EOG and EEG correlation. Wavelet Transform and Adaptive filtering [1] has efficiently removed artifacts from REM with a high rate of accuracy. However, it delivers poor quality in more filtering processes. Ensemble learning [30] is suitable for real-time applications and provides a fast convergence rate. DWT and ANC [19] eliminate artifacts in the low-frequency band even when the frequency is overlapping with the EEG signal. Yet, it has some processing overhead issues. BSS-SVM [34] gives consistent results in removing eye-blinking artifacts. But, it shows low performance when dealing with large datasets. FLM [22] provides accurate results in removing the artifacts from the EEG signal. However, this model may have a chance to fall into the local minima problem. ICA-ANC [5] gives better performance in artifacts removal from EEG with the use of parallel cleaning procedures. However, it shows weak performance in following the changes during online analysis. Therefore, it is necessary to develop new methodologies to solve the above-mentioned challenges and to remove the ocular artifacts efficiently.

3 Proposed methodology

3.1 Proposed architecture

In recent years, the medical field has used EEG signals for several brain-related evaluations. Generally, the EEG signals have some drawbacks like diverse types of noise signals, low SNR
rate, overlapping of noise and artifacts, and non-linearity and stationary properties. Among those, artifacts are the most dangerous issue, which has the capability of degrading the efficiency of EEG signals. The artifacts in EEG signals may cause electronic saturation with high amplitude, which may affect the EEG signals and lead to provide improper results in BCI applications. Several types of artifacts can affect EEG signals in different ways. One of the most common types of artifacts is an ocular artifact. The ocular artifacts are caused due to the overlapping of EOG and EEG signals in terms of both time and frequency domains. The major drawback of ocular artifacts in EEG signals is that ocular artifacts are 10 to 100 times stronger than EEG signals. Hence, it is considered a challenging task to remove ocular artifacts from EEG signals. Various techniques are used to identify and remove the ocular artifacts from EEG signals like DWT, ICA, PCA, BSS, FLM, etc. Although these techniques provide reasonable results in the process of recognizing and removal of artifacts, they also have some limitations like can’t remove the artifacts completely with a high accuracy rate, needing additional EOG recordings, requiring multi-channel EEG signals, etc. Therefore, the deep learning techniques [40, 43] are used in this paper to achieve accurate results with efficient diagnosis and mitigation process of ocular artifacts from EEG signals. The diagrammatic representation of the proposed detection and mitigation of ocular artifacts from EEG signals is depicted in Fig. 1. Figure 1 explains the

| Author          | Methodology       | Features                                                | Challenges                                                      |
|-----------------|-------------------|---------------------------------------------------------|****************************************************************|
| Sai et al. [27] | SVM               | • Improves efficiency in the identification of artifacts. | • Needs a large number of features for training data sets when   |
|                 |                   | • Offers better artifact removal without much degrading   | dealing with large datasets with more noise.                    |
|                 |                   | the time and frequency resolution of the signal.         |                                                            |
| Mosquera et al. [17] | RLS-ICA          | • This method is stable and provides a fast convergence  | • This method is not suitable for online analysis of EOG and  |
|                 |                   | rate.                                                   | EEG correlation.                                              |
|                 |                   | • Improves performance in artifacts removal and independent|                                                            |
|                 |                   | noise removal, without calibration.                      |                                                            |
| Betta et al. [1] | Wavelet Transform  | • Efficiently removes artifacts from REM with a high     | • Delivers poor quality in the mere filtering process.        |
|                 | and Adaptive      | rate of accuracy.                                       |                                                            |
|                 | filtering         |                                                         |                                                            |
| Selvan et al. [30] | Ensemble learning | • This technique is suitable for real-time applications  | • This model makes probing issues which leads to inaccurate    |
|                 |                   | • Provides fast convergence rate                         | results.                                                      |
| Peng et al. [19] | DWT and ANC       | • Eliminates artifacts in the low-frequency band even   | • This model has some processing overhead issues.              |
|                 |                   | when the frequency is overlapping with the EEG signal.   |                                                            |
| Shoker et al. [34] | BSS-SVM           | • This model gives consistent results in removing eye-    | • Shows low performance when dealing with large datasets.     |
|                 |                   | blinking artifacts.                                     |                                                            |
| QuaziS et al. [22] | FLM               | • Provides accurate results in removing the artifacts    | • This model may have a chance to fall into the local minima   |
|                 |                   | from EEG signals.                                       | problem.                                                      |
| Jafarifarmand et al. [5] | ICA-ANC           | • The parallel cleaning procedure of this algorithm      | • It shows weak performance in following the changes during   |
|                 |                   | gives better performance in artifacts removal from EEG.  | online analysis.                                              |

Table 1 Features and challenges of existing models for detecting and mitigating the artifacts from EEG signal
steps for the proposed architecture for detection and mitigation of ocular artifacts from EEG signals. The detailed description for Fig. 1 is listed given below.

The proposed ocular artifacts diagnosis model has two phases “(i) Detection phase and (ii) Mitigation phase”. The detection phase consists of three processes such as, “signal decomposition, feature extraction, and ocular artifacts detection”. Initially, the raw EEG input signals are decomposed by two decomposition techniques such as the 5-level DWT and Pisarenko harmonic decomposition technique. The input EEG signal [9] is decomposed into the number of samples and the samples are examined one by one for efficient processing. Then, the decomposed signals are given as the input for PCA [18] and ICA, in which the features are extracted from the decomposed signals. This helps to reduce the redundant features. The features extracted from the PCA and ICA are concatenated and forwarded to a deep learning technique namely optimized DCN, in which the epoch and learning rate are optimized using
Distance Sorted EFO (DS-EFO). The optimized DCN is trained to classify the signals from the extracted features. Therefore, the trained optimized DCN by DS-EFO provides the output as a signal with artifacts and a signal without artifacts. The objective function in terms of precision and accuracy ensures the efficient detection of ocular artifacts among the input and detected artifact signals. The mitigation phase has initiated once the ocular artifacts are detected in the first phase. The mitigation phase has various steps like “signal decomposition, signal denoising, and signal recovery”. The semi-simulated data are generated for the signals with ocular artifacts and it is divided into decomposed signals and leftover signals by using the EMCD decomposition technique. The decomposed signal is forwarded to the optimized DCN by DS-EFO for producing the denoised signals, which is further processed through inverse EMCD to generate artifacts restored denoised signal. Then, the artifacts removed signals or retrieved signals are generated by summing the leftover signals and the restored denoised signal. Here, the objective function of lifting the efficiency of mitigation of ocular artifacts among the clean signal and retrieved signal is to reduce the MAE between them.

3.2 Dataset description

This data set consists of EEG data from 9 subjects. The dataset used for validating the proposed model was gathered from (URL: http://www.bbci.de/competition/iv/#datasets, Access date: 2021-06-22). The proposed model for the detection and mitigation of ocular artifacts from EEG signals was implemented using MATLAB 2020a. The subjects were right-handed, had normal or corrected-to-normal vision, and were paid for participating in the experiments. All volunteers were sitting in an armchair, watching a flat-screen monitor placed approximately 1 m away at eye level. For each subject, 5 sessions are provided, whereby the first two sessions contain training data without feedback (screening), and the last three sessions were recorded with feedback.

3.3 Signal decomposition phase

The initial step of efficient signal processing is signal decomposition [26], in which the signal components are extracted and separated into more samples. The first phase of decomposition of input EEG signal $S_n$ is done by 5-level DWT. The collected input EEG signals are termed as $S_n$, where $n = 1, 2, \cdots, N$ and $N$ represent the total number of input EEG signals.

Discrete wavelet transforms (DWT) [31] It is a wavelet transform technique that decomposes the input EEG signals into many samples, where each sample is a time series of coefficients. The coefficients describe the signal evolution time related to the frequency bands. The frequency of the signal is divided into low and high-frequency bands by DWT. The low-frequency band is further divided into low and high-frequency phrases. The high-frequency band contains the data of the edge and surface of the signal. In the 5-level DWT decomposition method, the level 1 decomposition of the signal has produced four sub-frequency bands like LFLF1, LFHF1, HFLF1, and HFHF1. The LFLF1 sub-frequency band in the top level is given as input for the next level’s decompositions. The decomposition process of the remaining levels is as follows:

- For the decomposition of level 2, the DWT is employed to an LFLF1 sub-band, which is the previous level. The level 2 decomposition generates four sub-frequency bands such as LFLF2, LFHF2, HFLF2, and HFHF2.
Likewise, the level 3 decomposition produces 4 sub-bands such as LFLF3, LFHF3, HFLF3, and HFHF3 by applying the DWT to the LFLF2 i.e., level 2.

To the level 4 decomposition, the DWT is applied to level 3 i.e., the LFLF3 band. Therefore, the level 4 decomposition delivers four sub-frequency bands such as LFLF4, LFHF4, HFLF4, and HFHF4.

Finally, the decomposition of level 4 is done by applying DWT to the LFLF4 band. Level 4 generates four sub-frequency bands like LFLF5, LFHF5, HFLF5, and HFHF5.

The signal is transmitted to the filter series for the measurement of the DWT of a signal $sdt$. Initially, the samples are transmitted through a low pass filter with the impulse response $flp$. The result is generated as shown in Eq. (1).

$$F[g] = (sdt*flp)[g] = \sum_{m=-\infty}^{\infty} sdt[m]flp[g-m]$$  \hspace{1cm} (1)

Similarly, the high pass filter $fhp$ is also used for signal decomposition. The output of the low-pass filter is re-sampled by 2. So, the signal is again transferred to a new “low-pass filter and high-pass filter” for further processing by half the cut-off frequency of the final one. The process is defined in the formulas of Eq. (2) and Eq. (3).

$$F_{low}[g] = \sum_{m=-\infty}^{\infty} sdt[m]fhp[2g-m]$$  \hspace{1cm} (2)

$$F_{high}[g] = \sum_{m=-\infty}^{\infty} sdt[m]fhp[2g-m]$$  \hspace{1cm} (3)

Hence, the decomposed signal $S_n^{DWT}$ is generated by using the DWT technique.

**Pisarenko harmonic decomposition [2]** The next phase of decomposition $S_n^{DWT}$ is accomplished by Pisarenko harmonic decomposition technique. Generally, this technique is familiar for frequency estimation, in which the eigenvector $e^k$ corresponding to the lowest eigen value $e^H$ of the input signal is used for evaluation and the result is generated as shown in Eq. (4).

$$P_{phh}(e^k) = \frac{1}{|e^H n_{v_{min}}|^2}$$  \hspace{1cm} (4)

Here, the term $n_{v_{min}}$ refers to the noise eigenvector, where $e = [1, e^k, e^{2k}, \ldots, e^{(M-1)k}]^T$. Thus, the decomposed signal $S_n^{PHH}$ is generated by using Pisarenko harmonic decomposition technique.

### 3.4 Proposed DS-EFO

The detection and mitigation of ocular artifacts are effectively improved by the developed heuristic EFO algorithm namely DS-EFO. The DCN technique is used to detect and mitigate the artifacts in the signals. The parameters of DCN such as epoch and learning rate are optimized by the DS-EFO algorithm to improve the efficiency of detection. EFO algorithm is based on swarm intelligence. This algorithm has done many optimizations on the swarm intelligence and it is a better algorithm to solve some complex problems. However, it needs
more steps for solving the problems thereby it takes much time for computation. Therefore, the DS-EFO is proposed to overcome the limitations of the existing EFO by simplifying the process thereby reducing the computation time.

EFO [44]: EFO is simulated based on the communication behaviors of electric fish namely nocturnal electric fish. Generally, these electric fish live in the muddy water surface, where the visual capacity of electric fish is narrow. This electric fish with poor eye sight depends on their species-specific ability known as electrolocation to recognize the environment. Electrolocation refers to the sense of the ability of the electric fish to differentiate among prey and obstacles. There is an electric organ in the electric fish, which has the disc-like-cells called electrolytes. This organ is located at the tail of electric fish and it is used to generate an electric field. Electric Organ Discharge (EOD) is generated due to the simultaneous excitation of these electrolytes. EOD is identified by its amplitude and frequency. The amplitude of the electric field finds the effective range of the EOD in local search and this parameter depends on the size of the fish. The electric fish which are closest to the optimal source generates a high frequency of electric field and the time corresponding to the frequency \( f_{\text{ref}} \) is measured for each individual. The electrolocation is categorized into active and passive based on the capability of the fish in searching and locating the prey. The active electrolocation has limited range, the electric fish can able to sense the near areas to identify their prey and generate EOD through the changes in the electric field. On the other hand, passive electrolocation has a wider range than the active electrolocation, which leads the electric fish to find the location of the distanced object and be able to communicate with other fish. Thus, to find the best food source quality from the infinite food source of each individual with the time-frequency \( t_f \) in the large dimensional search space. The computational steps of the EFO algorithm are formulated in the following equations.

In the conventional EFO algorithm, the solutions are updated based on different constraints and that leads to computational and time complexity. Therefore, the proposed DS-EFO algorithm is introduced based on the distance among the solutions. It is executed by only one constraint called distance, which makes the algorithm a simpler one. Here, the distance is computed between the best solutions and current solutions. The proposed model has developed above-mentioned improvements. Then, the mean distance is computed. If the distance of the current solution is lesser than the mean distance and there exists at least one neighbor in the active sensor area, then the solutions are updated based on active electrolocation. If the condition fails, then the solutions are updated based on passive electrolocation.

**Population initialization** The collection of individuals or electric fish population is randomly spreading in the search space. The population initialization with the determination of boundaries is formulated in Eq. (5).

\[
x_{zp,q} = x_{\min,q} + \delta(x_{\max,q} - x_{\min,q})
\]  

(5)

Here the term \( x_{zp,q} \) refers to the location of the individual \( p \) in the dimensional search space with the population of size \(|NP|\), where \( p = 1, 2 \cdots (|NP|) \). The term \( \delta \) denotes the uniform distribution. The lower and upper boundaries of search space are indicated by \( x_{\min,q} \) and \( x_{\max,q} \) respectively.

After the population initialization process, the probability of individuals’ frequency range \( f_{\text{ref},p}^{\text{fr}} \) is determined using the minimum frequency \( f_{\text{min}}^{\text{fr}} \) and maximum frequency \( f_{\text{max}}^{\text{fr}} \) range of individuals from its fitness value. The individuals with a higher frequency range use active electrolocation, and others employ passive electrolocation. The frequency value of individuals
from its fitness value is formulated in Eq. (6).

\[
fr_tf^p = fr_{\text{min}} + \left( \frac{fr_{\text{worst}} - fr_{\text{best}}^p}{fr_{\text{worst}} - fr_{\text{best}}} \right) (fr_{\text{max}} - fr_{\text{min}})
\]  

(6)

Here, the terms \(fr_{\text{best}}^p\) and \(fr_{\text{worst}}^p\) denotes the best and worst fitness value of individuals for the corresponding individual population at iteration \(tf\). The probability calculation is done by using the frequency value of \(fr_{\text{min}}\) and \(fr_{\text{max}}\) which is given in the range of 0 and 1, respectively. Next, the amplitude value of the individual \(amp_p\) is calculated by the weight of the previous amplitudes \(\beta\) of individuals due to its dependence. The amplitude value depends on other passive electrolocation fish and the electric field strength decreases with the inverse cube of the distance. The calculation of amplitude value is formulated in Eq. (7).

\[
amp_{tf}^p = \beta amp_{tf}^{p-1} + (1-\beta)fr_{tf}^p
\]  

(7)

**Active electrolocation** The characteristics of active electrolocation determine the exploitation capability. The amplitude value \(amp_p\) determines the active range of the individual \(arp\) and it is formulated in Eq. (8).

\[
arp = (xz_{mzpq}-x_{\text{minq}})amp_p
\]  

(8)

After the calculation of the active range, the distance among the individuals \(p\) and the remaining population is measured. The Cartesian distance calculation is used to determine the individuals \(p\) and neighboring individuals \(kn\) and it is formulated in Eq. (9).

\[
dis_{pkn} = \sqrt{\sum_{q=1}^{\text{dis}} (xz_{p,q}-x_{znq})^2}
\]  

(9)

The EFO algorithm uses the Eq. (10) formula when at least one neighbor exists in the active region.

\[
x_{zpq}^{\text{new}} = x_{zpq} + \delta ar_p
\]  

(10)

**Passive Electrolocation** The exploration capability is based on the characteristics of passive electrolocation. The probability of the individual \(p\) in active mode (i.e., \(p \in NP_a\)) being perceived by the individual \(kn\) in passive mode (i.e., \(nk \in NP_{nk}\)) is calculated using Eq. (11).

\[
ab_p = \frac{amp_p}{\sum_{q \in NP_a} dis_{pq} amp_q}
\]  

(11)

Using Eq. (11) the individuals \(NK\) selected from \(NP_{amp}\) to determine a reference location in Eq. (12). The new location \(xyz_{pq}\) is generated in Eq. (13).

\[
xyz_{pq} = \sum_{nk=1}^{NK} \frac{amp_{nk} x_{znk,q}}{\sum_{nk=1}^{NK} amp_{nk}}
\]  

(12)
Finally, the probability of the new location is increased by modifying a parameter of the individual $p$ and it is formulated in Eq. (14).

$$x_{pq}^{new} = x_{pq} + \delta(xyz_{pq} - xz_{pq})$$  \hspace{1cm} (13)

$$x_{pq}^{nand} = x_{minq} + \delta(xz_{minq} - xz_{minq})$$  \hspace{1cm} (14)$$

In the EFO algorithm, the calculation of active and passive electrolocation takes several steps to find the distance among the individuals and the location of the best food source in the given search space. In the proposed algorithm, Eq. (10) and Eq. (14) are modified to reduce the time complexity and the computation time. The pseudo-code of the proposed DS-EFO algorithm is represented in Algorithm 1.

| Algorithm 1: Proposed DS-EFO algorithm |
|----------------------------------------|
| Population initialization $NP$ |
| The fitness value of each individual is calculated. |
| Frequency $f_p$ and amplitude $amp_p$, calculation of every individual using Eq. (6) and Eq. (7). |
| for each $p \in NP$ does |
| If $dis(p) < mean(dis)$ |
| Calculate the location of the best optimal food source on active electrolocation mode. |
| Determine active range $ar_p$, individual $p$ |
| Estimate the distance between individual $p$ and other individuals. |
| Else |
| Calculate the location of the best optimal food source on passive electrolocation mode. |
| Considering $ab_p$ values and choosing $NK$ individuals from $NP$, using Eq. (11). |
| Modify qth parameter by Eq. (14). |
| End |
| Evaluate the quality of the new source |
| Update frequency and amplitude values of the population $NP$ |
| End |

The flowchart of the proposed DS-EFO algorithm is represented in Fig. 2. The initial step is to assign the population of electric fish. The next step is to calculate the fitness for each individual. Then calculate the amplitude and frequency of each individual. If the distance calculation is higher than the mean values it can calculate the position of food source in active electro location or else calculate the position of food source in passive electro location. Update the frequency and amplitude of the population. Finally, the algorithm can be terminated after obtaining the optimal solution.
3.5 Ocular artifacts detection by optimized deformable convolutional networks

3.5.1 Feature extraction by PCA and ICA

The feature extraction process refers to transforming the input signals into numerical features for preserving the information of input data while processing. The results obtained are better while performing detection or classification tasks using the extracted features than applying to the raw input data. The features of decomposed signals $S_{n}^{PH}$ are extracted by two analytic component techniques such as PCA and ICA.

PCA [36] It is considered as a data reduction technique and it uses linear algebra for feature extraction, which transforms the input data signal $S_{n}^{PH}$ into compressed form, i.e., a small number of relevant features.
The features of decomposed signals are represented as $F_{fs}^{PCA}$ where $fs = 1, 2 \ldots FS$ and $FS$ denote the total number of features extracted from PCA, which are attained 83 features.

ICA [23] It is a method for extracting features from the input signal $S_n^{PH}$, which is a multivariate random signal that has transformed into independent components. Each component carries information that will not infer with others. Numerically, the probability of each component is obtained for the feature extraction process.

The features of decomposed signals using ICA are represented as $F_{fs}^{ICA}$, which is attained as 83 features.

Thus, the extracted features from PCA and ICA are concatenated as $E_{fs}^{ex} = \left\{ F_{fs}^{PCA}, F_{fs}^{ICA} \right\}$, where $fs = 1, 2 \ldots FS$ and $FS$ denote the total number of concatenated features.

3.5.2 Optimized DCN-based detection process

The efficient ocular artifacts detection is performed by DCN, which is further improved by optimizing the epoch $E_{ch}$ and learning rate $L_{er}$ of DCN using the proposed DS-EFO algorithm. The extracted features from PCA and ICA $E_{fs}^{ex}$ are given as input to the optimized DCN. The optimized DCN classifies the signals with or without ocular artifacts.

DCN [42] The deformable network is established to overcome the performance limitations of existing CNN [32]. The DCN network has learnable and deformable convolution and pooling layers. The deformable convolution adds offsets to the regular grid sampling locations in the standard convolution to deform the constant receptive field of the previous activation unit. Likewise, the deformable pooling adds an offset to each position in standard pooling. The preceding feature map is used to extract the offsets.

Deformable convolution The convolution layer is the key component of CNN, which is used for extracting feature maps from the input. The two steps of regular convolution are sampling and summation. The sampling is done on the input feature map by adding the offsets to the locations in regular convolution and the summation is processed by using weighted kernel values. The process of feature extraction is enhanced by generating deformed sampling locations for existing convolution. It is modified by adding 2 modules before regular convolution, in which one is used to produce an offset field and the other is used to generate deformable feature maps. The offset fields of the instantaneous value of the input signal through convolution are calculated and the information of neighboring instantaneous values is fused to generate the deformable signal. The extracted features $E_{fs}^{ex}$ are given as input to the DCN. The sampling locations are shifted to neighboring locations by training the offsets fields, which are generated using the weights of the convolution layer. The output generated from the deformable features using regular convolution is formulated in Eq. (15).

$$c_y(i,n) = \sum_{i=1}^{NT} w_{c_{it}}E_{fs}^{ex}(it)$$ (15)
Here, $w_{c,t}$ is the kernel weight. The deformable convolution considers fractional data locations and also the inter neuron positions, which is not considered in regular convolution. Moreover, the deformable convolution has no fixed shape.

**Deformable pooling** In conventional pooling, downsampling is used to minimize the size of input values to speed up the learning process. The fixed sampling locations and less efficiency of learnable process are the drawbacks of existing convolution. The limitations of both the methods are solved by the deformable Region-of-Interest (RoI) pooling. Before pooling, the offsets are added to the spatial positions and the kernel weights of the downsampling are trained well by using the deformable sampling locations. The functions of deformable convolution and deformable pooling are depicted in Fig. 3.

Figure 3 the DCN consists of a deformable pooling layer preceded by a deformable convolution layer. The deformable signal is generated by applying the linear interpolation method to the input signal. The deformable signal is further given to the convolution. The calculation of trainable offset is performed on both pooling and convolution layers.

**Deformable convolution layer** In the existing convolution method, the output features $c_y$ for each time instant $i_0$ are defined as shown in Eq. (16).

$$c_y(i_0) = \sum_{i_{nt}} w_c(i_{nt})E f_{ext}(i_{t_0} + i_{nt})$$  \quad (16)

Here, $i_t$ denotes the time instants of the sampling grid $SG$. The regular grid $SG$ is attached with offsets $\Delta i_{nt} \mid nt = 1, 2 \cdotsTN$. 

![Fig. 3 Functions of Deformable convolution and Deformable Pooling](image-url)
\[
\text{cy}(i_0) = \sum_{it} wc(it_{nt}) E_{f_{fs}^{ex}}(i_0 + it_{nt} + \Delta it_{nt}) 
\]

(17)

In Eq. (17), the term \(it_{nt} + \Delta it_{nt}\) refers to indicate the changeable sampling locations. The term \(\Delta it_{nt}\) is typically fractional and the linear interpolation method is used to find the new location. The equation is denoted in Eq. (18).

\[
E_{f_{fs}^{ex}}(it) = \sum_v GS(v, it) E_{f_{fs}^{ex}}(v) 
\]

(18)

Here, the fractional location is denoted by \(it\) and \(it = i_0 + it_{nt} + \Delta it_{nt}\), the term \(v\) denotes the spatial locations in the feature map \(E_{f_{fs}^{ex}}\), and the linear interpolation kernel is indicated by \(GS(v, it)\) and it is represented in Eq. (19).

\[
GS(v, it) = \max(0, 1-|v-it|) 
\]

(19)

Therefore, the computation time is reduced by using deformable convolution when compared to regular convolution. Additionally, the kernels in the convolution layer, as well as the offsets, are learned efficiently while training. The regular sampling method of the convolution layer is replaced with adaptive sampling to achieve enhanced learning.

**Deformable pooling layer** This layer uses spatial pooling, which concatenates the neighboring locations and generates a summation of the joint distribution of the features. As already known that the existing pooling models are not trained and their sampling location is fixed, the RoI pooling is used in the deformable pooling layer. The generated output is as shown in Eq. (20).

\[
cy(it) = \frac{\sum_{it} \text{cy}(i_0 + it_{nt} + \Delta it_{nt})}{nt} 
\]

(20)

**Fully connected layer** This layer is used to determine every class of signal and it is shown in Eq. (21).

\[
cy = \sigma(cywc_{fcl} + bs_{fcl}) 
\]

(21)

Here, the term \(wc_{fcl}\) and \(bs_{fcl}\) denotes the weight vector and bias in a fully connected layer and the term \(\sigma\) indicates the signum function. The overall architecture of the DCN is represented in Fig. 4.

The detection of ocular artifacts by optimized DCN generates the output as a signal with ocular artifacts or without artifacts from the raw input EEG signals. In the detection process, the optimized DCN is trained by assigning the input as extracted features \(E_{f_{fs}^{ex}}\) and the target the presence of ocular artifacts or not. This trained optimized DCN efficiently detects the ocular artifacts with concerning accuracy and precision.
3.6 Prevention of ocular artifacts by EMCD and optimized deformable convolutional networks

3.6.1 Semi-simulation data generation

The prevention or mitigation phase of ocular artifacts from EEG signals uses the same architecture model of DCN as in the detection phase. Here, the optimized DCN has been used in the process of denoising the signals. The detected ocular artifacts from the detection phase are further removed or prevented in the mitigation phase. However, there is no proof for the complete removal of ocular artifacts from the signals. The semi-simulated data generation is required to validate the removal process. The signals are added with some ocular artifacts are combined along with the signals with no artifacts. The signals without adding artifacts are considered as target signals $SM_{n}^{\text{in}}$ and the signals after removing ocular artifacts are assigned as the denoised signal $SM_{n}^{\text{dnoise}}$.

The 22 EEG and 3 EOG signals of 25 channel signals from BCI competition IV Dataset. Then it was segmented and reshaped with 288 epochs of length 6 s (250 Hz × 6 s = 1500 time points), and data tensor $X \in \mathbb{R}^{25 \times 1500 \times 288}$, respectively [7]. Further, the labeled data of whether the artifact-contaminated epochs or cleaned epochs are obtained from BCI competition. Additionally, the epochs with contaminated artifacts are reshaped for the matrix $XY_{\text{EEG} + \text{Arfats}} \in \mathbb{R}^{25 \times (1500N_{\text{epoch}})}$. Here, the contaminated epochs are denoted as $N_{\text{epoch}}$.

3.6.2 EMCD-based signal decomposition

The signal decomposition process involves the extraction of samples from the signal components. In the mitigation phase, the EMCD decomposition technique is used to decompose the artifactual signals into decomposed signals and leftover signals.
The decomposition algorithm of EMCD calculates the superior and inferior envelopes of signal decomposition in every process. In this process, the mean curve is extracted by optimizing the envelopes by averaging them using the scale control algorithm. This EMCD algorithm uses a data-driven approach and the time series are decomposed at the multi-scale level. Initially, the maxima and minima are extracted from the input time series. Then, the inferior and superior envelopes are generated by using the local scale control technique. The mean curve output is calculated using averaging both envelopes.

Consider \( SM^n_M \) as \( \{f_x(t), t = 1, \cdots, T\} \) where \( T \) is an element and the time series is referred by \( f(t) \). The minima series \( f_x(t) \) is denoted as \( \{k_{bi}, f_x[k_{bi}]\}, i = 1, \cdots, T_{kb} \) . The time index is indicated by \( k_{bi} \), and the number of minima is termed as \( T_{kb} \). The maxima series \( f_x(t) \) is denoted as \( \{ma_i, f_x[ma_i]\}, i = 1, \cdots, T_{ma} \) , in which the term \( ma_i \) indicates the time index and \( T_{ma} \) denotes the number of maximum. The term \( W\{(f_x(t_i), l_{x_i}\}, f_x[0]\) is the mostly utilized B-spline interpolation function that interpolates the input series \( (f_x(t_i), l_{x_i}) \) at time point \( f_x[0] \).

**Superior envelope**
The upper trend curve is referred to as the time series of this envelope that passes through all of its maxima. The maxima are interpolated by applying the B-spline interpolation. The superior envelope is mathematically represented in Eq. (22).

\[
f_x^{sup}[t] = W\{(ma_i, f_x[ma_i], f_x[t]\}, t = 1, \cdots, T
\]  

**Inferior envelope**
The inferior envelope of a time series is the lower trend curve that passes through all of its minima. The B-spline interpolation is used to interpolate the minima. The mathematical representation of the inferior envelope is represented in Eq. (23).

\[
f_x^{inf}[t] = W\{(kb_i, f_x[kb_i], f_x[t]\}, t = 1, \cdots, T
\]  

**Mean curve**
The mean curve of the time series is the average of its inferior and superior envelopes and it represents the global trend as shown in Eq. (24).

\[
f_x^{mean}[t] = \frac{f_x^{sup}[t] + f_x^{inf}[t]}{2}, t = 1, \cdots, T
\]  

**Mode**
The mode of a time series is the average of the number of its maxima \( T_{ma} \) and that of its minima \( T_{kb} \). The equation of the mean curve is formulated in Eq. (25).

\[
md(f_x[t]) = \left(\frac{T_{ma} + T_{kb}}{2}\right)
\]  

**Empirical waveform**
In reality, the mean curve is defined by the extrema that generate a new method to model the time series. The new concept EWF is introduced, which is the series of alternating maxima and minima. The empirical waveform is mathematically represented in Eq. (26).

\[
empw(f_x[t]) = \{(ma_i, f_x[ma_i]), (kb_i, f_x[kb_i])\}
\]
EWF is used to represent the mean curve when the mode of $md(fx(t))$, which characterizes this EWF. In particular, one entire sine wave cycle has one maximum and one minimum that contribute exactly one to its mode. Therefore, the EWF mode behaves like the count of entire cycles in classical Fourier analysis. Eq. (27) represents the empirical period mentioned EWF.

$$EP_{EWF} = \frac{T}{md(fx(t))}$$  \hspace{1cm} (27)

The equation for empirical frequency is represented in Eq. (28).

$$FP_{EWF} = \frac{md(fx(t))}{T}$$  \hspace{1cm} (28)

It should be noted that both empirical period and empirical frequency are the temporal evaluations over the complete time series than the original model parameters as in the conventional Fourier analysis. These conditions improve the descriptive capabilities of the signals in an efficient way that broad signal classes from the oscillatory sources are designed, for example, brain regions, and neurons, those signals are similar, but not like sine waves. Hence, the Fourier analysis decomposes this type of time series into a collection of sine waves at various frequencies and the wavelet transform decomposes them into a set of wavelets at several frequencies and distinct temporal locations.

Therefore, the signals with detected ocular artifacts $SM^f_n$ and the semi-simulated data are processed through EMCD, in which the signals are decomposed into decomposed signals $SM^\text{decomp}_n$ and leftover signals $SM^\text{lefto}_n$ and it is formulated in Eq. (29).

$$SM^\text{emp}_n = \{SM^\text{decomp}_n, SM^\text{lefto}_n\}$$  \hspace{1cm} (29)

Further, the decomposed signals $SM^\text{decomp}_n$ are processed by optimized DCN for denoising the signals, which are forwarded to inverse EMCD to recover the restored source signals. Hence, the retrieved signals are obtained by adding the restored denoised signals with leftover signals.

### 3.6.3 Prevention of ocular artifacts by optimized DCN

The prevention or mitigation phase of ocular artifacts uses optimized DCN for removing the noise from the given input signals. The decomposed signals from the EMCD are further given as input to optimized DCN to denoise the signals. The optimized DCN is trained by assigning the input as decomposed signals $SM^\text{decomp}_n$ and the target as denoised signals $SM^\text{dnoise}_n$. This trained optimized DCN by DS-EFO performs the signal denoising process in an efficient manner. The denoised signals are further given to inverse EMCD to attain the restored denoised signals $SM^\text{rede}_n$. The leftover signals $SM^\text{lefto}_n$ and the restored denoised signals $SM^\text{rede}_n$ are concatenated to produce the artifacts removed signals or retrieved signals $SM^\text{retrv}_n$, which is the output signal of the mitigation phase without any artifacts. The equation is denoted in Eq. (30).

$$SM^\text{retrv}_n = SM^\text{rede}_n + SM^\text{lefto}_n$$  \hspace{1cm} (30)
3.6.4 Objective model for detection and prevention

The proposed ocular artifacts removal model consists of two phases such as detection and prevention of ocular artifacts from EEG signals. The efficiency of the proposed model is verified by validating the multi-objective function.

**Detection phase** Although the DCN performs efficiently in the detection process of artifacts, it has some limitations in terms of accuracy when dealing with a large number of training datasets. Therefore, in the proposed model, the epoch $E_{ch}$ and learning rate $Le_{rt}$ of DCN are optimized using DS-EFO, which is in the range of 10 to 20 and 0.1 to 0.9, respectively. The main objective of optimized DCN is to improve the classification or detection process concerning with maximization of accuracy ($accy$) and precision ($prcn$).

$$\text{fr}1 = \arg \min_{(E_{ch}, Le_{rt})} \left( \frac{1}{accy + prcn} \right)$$

Accuracy $accy$ is referred as “the nearness of the measurements to a specific value”. It is formulated in Eq. (32).

$$accr = \frac{(ta_p + ta_n)}{(ta_p + ta_n + fa_p + fa_n)}$$

Here, term $ta_p$ is denoted as true positives, $fa_p$ is denoted as false positives, $ta_n$ is denoted as true negatives and $fa_n$ is denoted as false negatives. Precision $prcn$ is referred as “the points that are stated to be positive especially it is used to declare what percentage of the points is truly positive” as denoted in Eq. (33).

$$prcn = \frac{ta_p}{ta_p + fa_p}$$

Therefore, the efficiency of the ocular artifacts’ detection is enhanced by the optimized DCN by DS-EFO.

**Prevention phase** The ocular artifacts removal model uses DCN for denoising the decomposed signals. The efficiency of DCN is improved by optimizing the DCN parameters by DS-EFO. The objective function of optimized DCN removing ocular artifacts from EEG signals is the minimization of MAE between the clean signal and the artifacts removed signal or retrieved signal. The MAE metric “compared the artifact reduction methods ability to represent artifact waveforms because it provides an intuitive interpretation of the reconstruction errors by remaining their original unit”. The equation of MAE is denoted in Eq. (34).

$$MAE = \frac{1}{NF} \sum_{ne=1}^{NF} \left| SM_{op}^{retrv} - SM_{n}^{c \, ln} \right|$$

Here, the time index is denoted as $ne$ and the term $NF$ denotes the time points. The term $SM_{n}^{c \, ln}$ indicates the clean signal. Thus the objective function for optimized DCN is given in Eq. (35).
\[ f_r^2 = \arg\min_{\{E_{\alpha}, L_r\}} (MAE) \quad (35) \]

Therefore, the proposed detection and removal model of ocular artifacts from EEG signals provides enhanced performance by optimizing the epoch and learning rates of DCN by DS-EFO algorithm. In the detection phase, the optimized DCN efficiently classifies the ocular artifacts by signals with artifacts and signals without artifacts. In the prevention phase, the input signals are denoised efficiently using the optimized DCN.

### 4 Results and discussion

#### 4.1 Experimental setup

The proposed model for the detection and mitigation of ocular artifacts from EEG signals was implemented using MATLAB 2020a, and the performance evaluation was conducted by the following measures. The dataset used for validating the proposed model was collected from (URL: http://www.bbci.de/competition/iv/#datasets, Access date: 2021-06-22). The experimental analysis was conducted by considering 9 subjects and the population size as 10, and the number of iterations performed as 100. The detection phase of the proposed DS-DFO-DCN was compared over the existing heuristic algorithms such as Particle Swarm Optimization (PSO) [28], Grey Wolf Optimization (GWO) [6], Dual Positioned Elitism-based Earth Worm optimization Algorithm-DCN (DPE-EWA-DCN) [21], and EFO [44] classifiers such as Neural Networks [13, 29], SVM [33], EMCD+DPE-EWA-LWT [21] and DCN [42].

#### 4.2 Performance measures

Various performance metrics are taken into account for evaluating the performance of detection and prevention of ocular artifacts model that is given below:

(a) Sensitivity: It measures “the number of true positives, which are recognized exactly”.

\[ Sen = \frac{ta_p}{ta_p + fa_n} \quad (36) \]

(b) Specificity: It measures “the number of true negatives, which are determined precisely”.

\[ Spe = \frac{ta_n}{fa_n} \quad (37) \]
(c) FPR: It is computed as “the ratio of the count of false-positive predictions to the entire count of negative predictions”.

\[
FPR = \frac{fa_p}{fa_p + ta_n} \tag{38}
\]

(d) FNR: It is “the proportion of positives which yield negative test outcomes with the test”.

\[
FNR = \frac{fa_n}{fa_p + ta_n} \tag{39}
\]

(e) NPV: It is the “probability that subjects with a negative screening test truly don’t have the disease”.

\[
NPV = \frac{fa_n}{fa_n + ta_n} \tag{40}
\]

(f) FDR: It is “the number of false positives in all of the rejected hypotheses”.

\[
FDR = \frac{fa_p}{fa_p + ta_p} \tag{41}
\]

(g) F1 score: It is defined as the “harmonic mean between precision and recall. It is used as a statistical measure to rate performance”.

\[
F1 \, score = \frac{2ta_p}{2(ta_p + fa_p + fa_n)} \tag{42}
\]

(h) MCC: It is a “correlation coefficient computed by four values”.

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\[ MCC = \frac{ta_p \times ta_n - fa_p + fa_n}{\sqrt{(ta_p fa_p)(ta_p + fa_n)(ta_n + fa_n)}} \]  

(i) Correlation Coefficient: It “considers the relative movements in the signals and then defines if there is any relationship between them”.

\[ corr = \frac{n\left(\sum SM_{op}^{retrv} SM_n^{ln} - \sum SM_{op}^{retrv} SM_n^{ln}\right)}{\sqrt{n\sum \left(\sum SM_{op}^{retrv}\right)^2 - \left(\sum SM_{op}^{retrv}\right)^2 \left(\sum SM_n^{ln}\right)^2}} \]  

(j) RMSE: RMSE “is a quadratic scoring rule that measures the average magnitude of the error. It’s the square root of the average of squared differences between prediction and actual observation”.

\[ RMSE = \sqrt{\frac{1}{NF} \sum_{ne=1}^{NF} \left| SM_{op}^{retrv} - SM_n^{ln} \right|^2} \]  

4.3 Performance analysis on MAE

The performance analysis of the proposed ocular artifacts detection and mitigation model on MAE is evaluated between the retrieved signal and clean signal in semi-simulated data generation. The proposed DS-EFO-DCN is compared with other heuristic algorithms in terms of MAE with 9 subjects that are depicted in Fig. 5. The proposed DS-EFO-DCN achieves a minimum error rate when gradually increasing the SNR rate from 0.5 to 1.5. The EFO-DCN and the DPE-EWA-DCN attain more or less similar MAE rates like the proposed DS-EFO-DCN while varying the SNR rate for all 9 subjects when compared with the PSO and GWO algorithms. In subject 2, the MAE of proposed DS-EFO-DCN for SNR value 1.5 is 46.15% better than PSO-DCN, 40% better than GWO-DCN, 16% better than DPE-EWA-DCN, and 27.59% better than EFO-DCN. Likewise, for all the subjects, the proposed DS-EFO-DCN attains minimum MAE values when compared with conventional algorithms for the prevention of ocular artifacts.
Fig. 5 Analysis of the proposed DS-EFO-DCN detection and mitigation of ocular artifacts with existing meta-heuristic algorithms in terms of MAE for (a) Subject 1, (b) Subject 2, (c) Subject 3, (d) Subject 4, (e) Subject 5, (f) Subject 6, (g) Subject 7, (h) Subject 8, and (i) Subject 9.
4.4 Performance analysis on RMSE

The performance of the DS-EFO-DCN is compared with the other heuristic algorithms by evaluating the RMSE value for all 9 subjects as shown in Fig. 6. The minimum error rate value has been attained by the proposed DS-EFO-DCN while increasing the SNR rate from the range of 0.5 to 1.5 when compared with the conventional algorithms. In all 9 subjects, the EFO-DCN and the DPE-EWA-DCN also reach more or less the same RMSE rate while varying the SNR rate like the proposed DS-EFO-DCN when compared with the PSO and GWO algorithms. In subject 9, the RMSE of proposed DS-EFO-DCN for SNR value 1 is 40% better than PSO-DCN, 50% better than GWO-DCN, 23.07% better than DPE-EWA-DCN and 45.45% better than EFO-DCN. Similarly, the proposed DS-EFO-DCN attains minimum RMSE values for the remaining subjects when compared with conventional algorithms for prevention of ocular artifacts.

4.5 Performance analysis on the correlation coefficient

The semi-simulated data generation is used to validate the mitigation of ocular artifacts since there is no proof to validate the measures. Therefore, the difference between the denoised and the clean signal is validated by autocorrelation evaluation. While processing the evaluation there should not be any data loss other than artifacts. Thus, the best performance is attained by reaching a high correlation coefficient value. The correlation coefficient of the proposed DS-EFO-DCN is attained maximum rate when compared with the conventional algorithms. The proposed DS-EFO-DCN is compared with other conventional algorithms with 22 numbers electrodes for each subject and the results regards to correlation coefficient for all the 9 subjects are represented in Table 2. From Table 2, while taking electrode 5 of subject 2, the performance of the proposed DS-EFO-DCN is 15.22% better than PSO-DCN, 44.92% better than GWO-DCN, 1.46% better than DPE-EWA-DCN, and 12.29% better than EFO-DCN. Therefore, the proposed approach has attained a high correlation coefficient, which improves the prevention strategy when compared to other algorithms.

4.6 Overall performance analysis of detection

The performance of the proposed DS-EFO-DCN detection and mitigation model is analyzed with the existing meta-heuristic algorithms and is represented in Table 3. The accuracy of the proposed DS-EFO-DCN model is 4.42% better than PSO-DCN, 0.82% better than GWO-DCN, 2.67% better than DPE-EWA-DCN, and 3.02% better than EFO-DCN. Similarly, the proposed model attains better performance for all the performance metrics. In the same way, the performance analysis on the proposed DS-EFO-DCN model with the existing classifiers is represented in Table 4. The precision of the proposed model is 24.44% better than NN, 5.97% better than SVM, 27% better than DPE-EWA-DCN, and 15.35% better than DCN. Therefore, the overall analysis reveals that the proposed DS-EFO-DCN algorithm of detection and mitigation model provides better performance than the existing algorithms.

4.7 Performance analysis on CSED

The performance of the DS-EFO-DCN is compared with the other heuristic algorithms by evaluating the CSED value for all 9 subjects as shown in Fig. 7. The minimum error rate value
Fig. 6 Analysis of proposed DS-EFO-DCN ocular artifacts detection and mitigation model over existing meta heuristic algorithms in terms of RMSE for (a) Subject 1, (b) Subject 2, (c) Subject 3, (d) Subject 4, (e) Subject 5, (f) Subject 6, (g) Subject 7, (h) Subject 8, and (i) Subject 9
Table 2  Performance Analysis after removing ocular artifacts without semi-simulated data generation in terms of the correlation coefficient for all 9 subjects

| Subject 2 | Electrodes | PSO-DCN [28] | GWO-DCN [6] | DPE-EWA-DCN [21] | EFO-DCN [44] | DS-EFO-DCN |
|-----------|------------|--------------|-------------|-------------------|---------------|------------|
| 1         | 0.8029     | 0.71993      | 0.92256     | 0.85061           | 0.98486       |
| 2         | 0.81406    | 0.6538       | 0.95376     | 0.8653            | 0.96245       |
| 3         | 0.83327    | 0.6974       | 0.92886     | 0.88644           | 0.97234       |
| 4         | 0.83058    | 0.68791      | 0.95274     | 0.90748           | 0.98819       |
| 5         | 0.83393    | 0.66305      | 0.94705     | 0.85573           | 0.96091       |
| 6         | 0.83634    | 0.66631      | 0.95317     | 0.85214           | 0.98423       |
| 7         | 0.82893    | 0.73296      | 0.95564     | 0.90317           | 0.98424       |
| 8         | 0.78008    | 0.61169      | 0.92531     | 0.86482           | 0.96145       |
| 9         | 0.78019    | 0.63918      | 0.93497     | 0.85053           | 0.97583       |
| 10        | 0.78525    | 0.66258      | 0.95726     | 0.8989            | 0.98735       |
| 11        | 0.79564    | 0.68226      | 0.9445      | 0.85843           | 0.96932       |
| 12        | 0.78137    | 0.72287      | 0.95406     | 0.90279           | 0.98339       |
| 13        | 0.80545    | 0.66567      | 0.93832     | 0.85572           | 0.97744       |
| 14        | 0.80046    | 0.66124      | 0.92054     | 0.87115           | 0.9829        |
| 15        | 0.81248    | 0.70447      | 0.94367     | 0.88561           | 0.98318       |
| 16        | 0.83557    | 0.66551      | 0.92878     | 0.88511           | 0.96144       |
| 17        | 0.79791    | 0.72052      | 0.94004     | 0.89006           | 0.96821       |
| 18        | 0.80029    | 0.66531      | 0.94755     | 0.88888           | 0.97895       |
| 19        | 0.83157    | 0.66973      | 0.94308     | 0.876             | 0.9742        |
| 20        | 0.80043    | 0.66824      | 0.94236     | 0.85839           | 0.98821       |
| 21        | 0.78829    | 0.63213      | 0.93647     | 0.89512           | 0.98171       |
| 22        | 0.81047    | 0.61198      | 0.92928     | 0.86451           | 0.97647       |

| Subject 3 | Electrodes | PSO-DCN [28] | GWO-DCN [6] | DPE-EWA-DCN [21] | EFO-DCN [44] | DS-EFO-DCN |
|-----------|------------|--------------|-------------|-------------------|---------------|------------|
| 1         | 0.79794    | 0.71007      | 0.94127     | 0.88333           | 0.97908       |
| 2         | 0.79537    | 0.70123      | 0.9559      | 0.90078           | 0.9858        |
| 3         | 0.83319    | 0.63904      | 0.94715     | 0.87448           | 0.96318       |
| 4         | 0.80681    | 0.68154      | 0.94581     | 0.87772           | 0.9727        |
| 5         | 0.82896    | 0.65894      | 0.95646     | 0.89958           | 0.96813       |
| 6         | 0.7859     | 0.61289      | 0.94946     | 0.90947           | 0.98857       |
| 7         | 0.83158    | 0.60336      | 0.94309     | 0.88144           | 0.97765       |
| Subject 4 | Electrodes | PSO-DCN [28] | GWO-DCN [6] | DPE-EWA-DCN [21] | EFO-DCN [44] | DS-EFO-DCN |
|----------|------------|---------------|--------------|-------------------|----------------|-------------|
| 1        | 0.8301     | 0.65879       | 0.93557      | 0.85848           | 0.97479        |             |
| 2        | 0.80816    | 0.63358       | 0.92469      | 0.85409           | 0.97437        |             |
| 3        | 0.80483    | 0.68367       | 0.93683      | 0.89285           | 0.97889        |             |
| 4        | 0.81016    | 0.66712       | 0.95416      | 0.86848           | 0.98157        |             |
| 5        | 0.78753    | 0.7258        | 0.93344      | 0.89027           | 0.96876        |             |
| 6        | 0.78794    | 0.73086       | 0.92457      | 0.88915           | 0.9626         |             |
| 7        | 0.83223    | 0.7145        | 0.94163      | 0.88186           | 0.98395        |             |
| 8        | 0.81618    | 0.69925       | 0.95325      | 0.89291           | 0.9713         |             |
| 9        | 0.79592    | 0.70405       | 0.93325      | 0.88029           | 0.98248        |             |
| 10       | 0.83189    | 0.72596       | 0.92159      | 0.87928           | 0.9652         |             |
| 11       | 0.78349    | 0.60913       | 0.92541      | 0.87987           | 0.96317        |             |
| 12       | 0.80747    | 0.64703       | 0.92291      | 0.90616           | 0.98625        |             |
| 13       | 0.82333    | 0.60061       | 0.94814      | 0.87336           | 0.98541        |             |
| 14       | 0.80034    | 0.71593       | 0.93735      | 0.85703           | 0.9899         |             |
| 15       | 0.80407    | 0.67104       | 0.94539      | 0.86443           | 0.98506        |             |
| 16       | 0.81162    | 0.65126       | 0.94657      | 0.89109           | 0.96107        |             |
| 17       | 0.83365    | 0.63173       | 0.94171      | 0.90036           | 0.9758         |             |
| 18       | 0.8267     | 0.67488       | 0.94389      | 0.90821           | 0.98893        |             |
| 19       | 0.78416    | 0.64053       | 0.95336      | 0.86291           | 0.97482        |             |
| 20       | 0.79673    | 0.60957       | 0.94517      | 0.89562           | 0.98533        |             |
| 21       | 0.80276    | 0.6119        | 0.95327      | 0.88505           | 0.96204        |             |
| 22       | 0.83188    | 0.60957       | 0.93777      | 0.87418           | 0.98864        |             |

| Subject 5 | Electrodes | PSO-DCN [28] | GWO-DCN [6] | DPE-EWA-DCN [21] | EFO-DCN [44] | DS-EFO-DCN |
|-----------|------------|---------------|--------------|-------------------|----------------|-------------|
| 1         | 0.83536    | 0.67416       | 0.92455      | 0.87149           | 0.97352        |             |
| 2         | 0.81386    | 0.71607       | 0.95618      | 0.90922           | 0.96755        |             |
| 3         | 0.80589    | 0.67166       | 0.95708      | 0.85504           | 0.97651        |             |
| 4         | 0.80027    | 0.67727       | 0.92117      | 0.86502           | 0.96721        |             |
| 5         | 0.82324    | 0.62986       | 0.93877      | 0.89868           | 0.96926        |             |
| 6         | 0.78082    | 0.68229       | 0.95278      | 0.85507           | 0.98641        |             |
| 7         | 0.80244    | 0.61999       | 0.92923      | 0.88188           | 0.98567        |             |
| 8         | 0.83536    | 0.60731       | 0.9517       | 0.89804           | 0.98304        |             |
| 9         | 0.81279    | 0.69566       | 0.95092      | 0.89433           | 0.98685        |             |
| 10        | 0.80843    | 0.6852        | 0.9439       | 0.8585            | 0.96519        |             |
| 11        | 0.80979    | 0.63075       | 0.92009      | 0.87627           | 0.97501        |             |
| 12        | 0.79854    | 0.65688       | 0.93443      | 0.87102           | 0.97818        |             |
| 13        | 0.83705    | 0.68819       | 0.95437      | 0.87871           | 0.98648        |             |
| 14        | 0.83892    | 0.67774       | 0.94585      | 0.88524           | 0.97926        |             |
| 15        | 0.81081    | 0.61786       | 0.9344       | 0.85875           | 0.97129        |             |
| 16        | 0.83956    | 0.62369       | 0.94401      | 0.90432           | 0.98146        |             |
| Subject 6 Electrodes | PSO-DCN [28] | GWO-DCN [6] | DPE-EWA-DCN [21] | EFO-DCN [44] | DS-EFO-DCN |
|---------------------|--------------|--------------|-------------------|---------------|------------|
| 1                   | 0.78713      | 0.62623      | 0.94365           | 0.87981       | 0.98541    |
| 2                   | 0.80281      | 0.67444      | 0.95791           | 0.85134       | 0.97769    |
| 3                   | 0.82877      | 0.6497       | 0.93966           | 0.85323       | 0.9659     |
| 4                   | 0.79465      | 0.64407      | 0.95764           | 0.85845       | 0.97508    |
| 5                   | 0.83307      | 0.70174      | 0.92861           | 0.90361       | 0.96156    |
| 6                   | 0.82276      | 0.67221      | 0.93512           | 0.87795       | 0.985      |
| 7                   | 0.80269      | 0.71069      | 0.94647           | 0.88365       | 0.97285    |
| 8                   | 0.79494      | 0.62683      | 0.92246           | 0.87967       | 0.97589    |
| 9                   | 0.79517      | 0.69493      | 0.94841           | 0.85407       | 0.97644    |
| 10                  | 0.82603      | 0.60735      | 0.93598           | 0.90386       | 0.97973    |
| 11                  | 0.78299      | 0.71216      | 0.95083           | 0.86731       | 0.97077    |
| 12                  | 0.82112      | 0.695        | 0.93443           | 0.86614       | 0.96227    |
| 13                  | 0.81722      | 0.73244      | 0.93212           | 0.88565       | 0.97323    |
| 14                  | 0.82486      | 0.61282      | 0.95747           | 0.87855       | 0.96139    |
| 15                  | 0.83864      | 0.72718      | 0.94729           | 0.8721        | 0.98141    |
| 16                  | 0.80303      | 0.67139      | 0.9357            | 0.88934       | 0.9611     |
| 17                  | 0.79561      | 0.68609      | 0.92375           | 0.90629       | 0.98767    |
| 18                  | 0.83265      | 0.64425      | 0.94791           | 0.88723       | 0.98153    |
| 19                  | 0.82837      | 0.61085      | 0.94422           | 0.86697       | 0.98719    |
| 20                  | 0.80767      | 0.71909      | 0.92281           | 0.86231       | 0.97489    |
| 21                  | 0.82997      | 0.69336      | 0.93077           | 0.89699       | 0.96155    |
| 22                  | 0.8236       | 0.60251      | 0.94593           | 0.89114       | 0.97528    |

| Subject 7 Electrodes | PSO-DCN [28] | GWO-DCN [6] | DPE-EWA-DCN [21] | EFO-DCN [44] | DS-EFO-DCN |
|---------------------|--------------|--------------|-------------------|---------------|------------|
| 1                   | 0.82554      | 0.64073      | 0.92643           | 0.86216       | 0.96702    |
| 2                   | 0.8396       | 0.63884      | 0.95618           | 0.86298       | 0.97625    |
| 3                   | 0.8014       | 0.60086      | 0.94064           | 0.90858       | 0.97777    |
| 4                   | 0.82517      | 0.65246      | 0.92955           | 0.88559       | 0.96872    |
| 5                   | 0.7866       | 0.66117      | 0.94199           | 0.86826       | 0.98315    |
| 6                   | 0.81582      | 0.6426       | 0.95479           | 0.90806       | 0.98307    |
| 7                   | 0.80584      | 0.64072      | 0.95403           | 0.90376       | 0.98265    |
| 8                   | 0.82384      | 0.63395      | 0.93834           | 0.8614        | 0.97018    |
| 9                   | 0.79567      | 0.73114      | 0.93682           | 0.85011       | 0.96157    |
| 10                  | 0.78569      | 0.72043      | 0.93185           | 0.89271       | 0.98055    |
| 11                  | 0.80706      | 0.65561      | 0.9221            | 0.90206       | 0.98879    |
| 12                  | 0.8184       | 0.66712      | 0.94864           | 0.8571        | 0.96471    |
| 13                  | 0.78792      | 0.6791       | 0.92501           | 0.85234       | 0.96329    |
| 14                  | 0.80717      | 0.66855      | 0.93353           | 0.88589       | 0.98647    |
| 15                  | 0.81913      | 0.63777      | 0.93504           | 0.88626       | 0.97397    |
| 16                  | 0.82962      | 0.73856      | 0.95365           | 0.88099       | 0.9847     |
| 17                  | 0.79848      | 0.62571      | 0.92081           | 0.85045       | 0.98349    |
| 18                  | 0.80414      | 0.72063      | 0.95208           | 0.89134       | 0.96542    |
| 19                  | 0.83305      | 0.60457      | 0.93095           | 0.90676       | 0.96717    |
| 20                  | 0.82203      | 0.64647      | 0.92951           | 0.90241       | 0.96157    |
| 21                  | 0.79451      | 0.70482      | 0.93856           | 0.8568        | 0.97766    |
| 22                  | 0.82559      | 0.69021      | 0.9477            | 0.87127       | 0.98254    |
has been attained by the proposed DS-EFO-DCN while increasing the SNR rate from the range of 0.5 to 1.5 when compared with the conventional algorithms. In subject 9, the CSED of proposed DS-EFO-DCN for SNR value 1 is 64.40% better than PSO-DCN, 35.59% better than GWO-DCN, 11.86% better than EMCD+DPE-EVA-LWT-DCN, and 35.59% better than EFO-DCN. Similarly, the proposed DS-EFO-DCN attains minimum CSED values for the remaining subjects when compared with conventional algorithms for the prevention of ocular artifacts.

Table 2 (continued)

| Subject 9 | Electrodes | PSO-DCN [28] | GWO-DCN [6] | DPE-EWA-DCN [21] | EFO-DCN [44] | DS-EFO-DCN |
|-----------|-------------|--------------|--------------|------------------|---------------|-------------|
| 1         | 0.83573     | 0.60952      | 0.94855      | 0.88807          | 0.97331       |
| 2         | 0.82393     | 0.7356       | 0.95159      | 0.87179          | 0.98497       |
| 3         | 0.82499     | 0.61383      | 0.95050      | 0.87446          | 0.97916       |
| 4         | 0.80444     | 0.67658      | 0.93243      | 0.87212          | 0.97026       |
| 5         | 0.79437     | 0.65642      | 0.95055      | 0.8781           | 0.97007       |
| 6         | 0.81125     | 0.61499      | 0.94045      | 0.8802           | 0.96736       |
| 7         | 0.79314     | 0.70138      | 0.93761      | 0.90463          | 0.98762       |
| 8         | 0.83054     | 0.68592      | 0.95119      | 0.86239          | 0.96865       |
| 9         | 0.81978     | 0.70962      | 0.95617      | 0.87032          | 0.96459       |
| 10        | 0.82897     | 0.67933      | 0.9229       | 0.88445          | 0.97048       |
| 11        | 0.82763     | 0.71358      | 0.94693      | 0.87922          | 0.98151       |
| 12        | 0.80815     | 0.68075      | 0.92893      | 0.86573          | 0.98047       |
| 13        | 0.79857     | 0.73216      | 0.93516      | 0.88478          | 0.98033       |
| 14        | 0.82125     | 0.722        | 0.93019      | 0.9027           | 0.96018       |
| 15        | 0.83921     | 0.67106      | 0.95164      | 0.85366          | 0.97086       |
| 16        | 0.82625     | 0.71044      | 0.95782      | 0.87645          | 0.98614       |
| 17        | 0.82977     | 0.66622      | 0.94469      | 0.85506          | 0.96923       |
| 18        | 0.82237     | 0.71603      | 0.94675      | 0.88379          | 0.97732       |
| 19        | 0.81572     | 0.64515      | 0.95543      | 0.88236          | 0.96864       |
| 20        | 0.82517     | 0.73666      | 0.94613      | 0.89608          | 0.96363       |
| 21        | 0.8098      | 0.63895      | 0.9416       | 0.86399          | 0.97126       |
| 22        | 0.83191     | 0.6102       | 0.93447      | 0.88524          | 0.98371       |
4.8 Performance analysis on PSNR

The performance of the DS-EFO-DCN is compared with the other heuristic algorithms by evaluating the PSNR value for all 9 subjects as shown in Fig. 8. The minimum error rate value has been attained by the proposed DS-EFO-DCN while increasing the SNR rate from the range of 0.5 to 1.5 when compared with the conventional algorithms. The peak signal-to-noise ratio (PSNR) is the better quality of the compressed or reconstructed signals. The MSE represents the cumulative squared error between the compressed and the original signal. PSNR represents a measure of the peak error. In subject 9, the PSNR of the proposed DS-EFO-DCN is, 11.76%, 7.843%, 5.882%, and 9.803 lower than PSO-DCN, GWO-DCN, EMCD+DPE-EWA-LWT-DCN, and EFO-DCN respectively for SNR value 1. Therefore, the proposed DS-EFO-DCN establishes better PSNR values when compared with conventional methods for the prevention of ocular artifacts.

4.9 Performance analysis on SDR

The performance of the DS-EFO-DCN is compared with the other heuristic algorithms by evaluating the SDR value for all 9 subjects as shown in Fig. 9. The minimum error rate value has been attained by the proposed DS-EFO-DCN while increasing the SNR rate from the range of 0.5 to 1.5 when compared with the conventional algorithms. The peak signal-to-noise ratio (PSNR) is the better quality of the compressed or reconstructed signals. The MSE represents the cumulative squared error between the compressed and the original signal. PSNR represents a measure of the peak error. In subject 9, the PSNR of the proposed DS-EFO-DCN is, 11.76%, 7.843%, 5.882%, and 9.803 lower than PSO-DCN, GWO-DCN, EMCD+DPE-EWA-LWT-DCN, and EFO-DCN respectively for SNR value 1. Therefore, the proposed DS-EFO-DCN establishes better PSNR values when compared with conventional methods for the prevention of ocular artifacts.
Fig. 7  Analysis of proposed DS-EFO-DCN ocular artifacts detection and mitigation model over existing meta heuristic algorithms in terms of CSED for (a) Subject 1, (b) Subject 2, (c) Subject 3, (d) Subject 4, (e) Subject 5, (f) Subject 6, (g) Subject 7, (h) Subject 8, and (i) Subject 9
Fig. 8 Analysis of proposed DS-EFO-DCN ocular artifacts detection and mitigation model over existing meta heuristic algorithms in terms of PSNR for (a) Subject 1, (b) Subject 2, (c) Subject 3, (d) Subject 4, (e) Subject 5, (f) Subject 6, (g) Subject 7, (h) Subject 8, and (i) Subject 9
Fig. 9 Analysis of proposed DS-EFO-DCN ocular artifacts detection and mitigation model over existing metaheuristic algorithms in terms of SDR for (a) Subject 1, (b) Subject 2, (c) Subject 3, (d) Subject 4, (e) Subject 5, (f) Subject 6, (g) Subject 7, (h) Subject 8, and (i) Subject 9.
range of 0.5 to 1.5 when compared with the conventional algorithms. A signal-to-distortion ratio (SDR) indicates that the signal level is greater than the noise level. PSNR represents a measure of the peak error. In subject 9, the SDR of the proposed DS-EFO-DCN is, 19.23%, 15.38%, 11.53%, and 17.30 lower than PSO-DCN, GWO-DCN, EMCD+DPE-EVA-LWT-DCN, and EFO-DCN respectively for SNR value 1. Therefore, the proposed DS-EFO-DCN establishes better SDR values when compared with other conventional methods for the prevention of ocular artifacts.

4.10 Comparative analysis on different classifiers

The comparative analysis of the proposed DS-EFO-DCN detection and mitigation model with the existing classifiers is represented in Table 5. The accuracy of the proposed DS-EFO-DCN model is 2.528%, 1.713%, and 3.589% enriched than BSS-SVM, FLM, and ICA-ANC respectively. Hence, it is proved that the comparative analysis of the proposed DS-EFO-DCN algorithm of detection and mitigation model provides progressed performance than the other conventional algorithms.

4.11 Analysis of misclassification results

The analysis of misclassification rates for the proposed DS-EFO-DCN model is shown in Table 6. “The misclassifications are defined to be a source detected as an artifact or an artifact detected as a source, and missed detections were defined as a source or artifact being detected as neither a source nor artifact”. It is evaluated by terms of confusion matrix as shown in Table 6. A true positive is an outcome, where the model correctly predicts the positive class. The proposed model achieves 70 true positive values that demonstrate the superiority of the detection model. A true negative is an outcome where the model correctly predicts the negative class. The proposed model attains 543 true negative values, which specifies the accurate detection of the suggested DS-EFO-DCN model. A false positive is an outcome, where the model incorrectly predicts the positive class. The proposed model occurs 30 false-positive values using suggested DS-EFO-DCN. A false negative is an outcome where the model incorrectly predicts the negative class to derive the performance of the designed model. The proposed model secured 6 false negative values. Misclassification is mostly occurring due to the same data characteristics, and the proposed DS-EFO-DCN fails at some point as shown in

| Measures      | BSS-SVM [34] | FLM [22] | ICA-ANC [5] | DS-EFO-DCN |
|---------------|-------------|-----------|-------------|------------|
| “Accuracy”    | 0.92065     | 0.92835   | 0.91063     | 0.94453    |
| “Sensitivity” | 0.92105     | 0.91447   | 0.91447     | 0.92105    |
| “Specificity” | 0.92059     | 0.93019   | 0.91012     | 0.94764    |
| “Precision”   | 0.61111     | 0.63596   | 0.57519     | 0.7        |
| “FPR”         | 0.079407    | 0.069808  | 0.089878    | 0.052356   |
| “FNR”         | 0.078947    | 0.085526  | 0.085526    | 0.078947   |
| “NPV”         | 0.92059     | 0.93019   | 0.91012     | 0.94764    |
| “FDR”         | 0.38889     | 0.36404   | 0.42481     | 0.3        |
| “F1-Score”    | 0.73327     | 0.7499    | 0.70591     | 0.79545    |
| “MCC”         | 0.71009     | 0.72585   | 0.6812      | 0.77369    |
Table 6: Confusion matrix for the proposed DS-EFO-DCN detection and mitigation model

| True Positive | True Negative | False Positive | False Negative |
|---------------|---------------|----------------|----------------|
| 70            | 543           | 30             | 6              |

Table 6, as the objective function does not focus on minimizing the misclassification rate. Hence, in the future, this can be extended by deriving a new fitness or objective function concerning the misclassification rate, thus ensuring the proper detection ability.

### 4.12 Results discussion

The suggested DS-EFO-DCN is a better algorithm to solve some complex problems and also it has a good exploitation capability, it obtained maximum accuracy, the error rate is low. Due to these advantages, the proposed DS-EFO-DCN performs better than the existing methods. The failure case of the proposed BU-SLnO-AP-CNN includes it does not apply for larger datasets, the time complexity is low. From the table results, the proposed model provides equal performance when compared with the existing model BSS-SVM. Therefore the performance is needed to be improved further to enhance the efficiency when compared with the other conventional methods. In clinical applications, the proposed detection and mitigation of ocular artifacts from EEG signal is recommended for better identification of non cerebral components. It should be mentioned that the ocular artifacts such as eye movement or blinks artifacts occur in the delta range 0–4 Hz. It is commonly known that the occurrence of delta activity in EEG data may provide clinically useful information about brain damage, some pathological conditions (e.g., brain tumor, Alzheimer’s disease), or psychiatric diseases (e.g., schizophrenia, depression).

### 5 Conclusion

In this paper, a new approach for the detection and mitigation of ocular artifacts from EEG signals was introduced. The proposed model has two phases such as detection phase and mitigation phase. In the detection part, the input EEG signals were decomposed through 5-level-DWT and Pisarenko harmonic decomposition techniques. The features of decomposed signals were extracted by PCA and ICA. Then, the extracted features were given to the optimized DCN, in which the optimization was done by the DS-EFO algorithm. The optimized DCN classified the signals into a signal with artifacts and without artifacts. In the mitigation part, the semi-simulated data was generated for validating the detection of artifacts. Here, the mitigation of ocular artifacts from EEG signals was done by the same optimized DCN using the proposed DS-EFO. The performance analysis on the proposed DS-EFO-DCN algorithm ensures the enhanced results over the existing meta-heuristic algorithms in terms of MAE, RMSE, and correlation coefficients. From the overall analysis, the specificity evaluation of the proposed DS-EFO-DCN model has achieved 5.03% better than NN, 0.93% better than SVM, 2.84% better than EMCD+DPE-EWA-LWT, and 3.23% better than DCN. Thus, it is concluded that the developed DS-EFO-DCN model achieves better performance in the detection and mitigation of ocular artifacts from EEG signals. The limitations of the proposed model is slight degradation in accuracy rate and also for the identification of ocular artifacts from EEG signals.
signals needs further improvement that are need to be improved for obtaining the efficient performance of the proposed model. In our research work is to optimize the existing algorithm DCN with DS-EFO for obtaining a better accuracy rate for the detection of ocular artifacts in the future utilized new detection techniques and also Dissolved Gas Analysis (DGA) can be considered as one of the significant detection methods to provide the enriched performance for the proposed model.

Declarations

Conflict of interest The authors declare no conflict of interest.

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