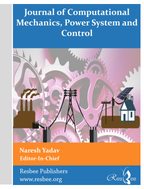
Resbee Publishers

Journal of Computational Mechanics, Power System and Control

Received 22 April, Revised 13 July, Accepted 20 July



Improved Chicken Swarm Optimization based NARX Neural Network: Artefacts Removal from ECG Signal

Shivchetan Sambaragimath
Cognizant, New Jersey, United States
Shivchetan.git@gmail.com

Abstract: One of the important research subjects is the Electrocardiogram (ECG) artecraft removal, which is the pure ECG signals that are an important segment to diagnosing heart-associated issues. ECG signals are extremely well-known to the communication for the other signals such as EEG, electromyogram (EMG) , as well as EOG signals and the intervention majorly, happens during the recording. In the ECG signals, because of the artefacts attendance, it has chaotic issues in eradicating the artefacts from the ECG signal for that a new approach is developed. The developed technique uses an adaptive filter called the Improved Chicken Swarm Optimization (ICSO) Algorithm and Levenberg Marqueret learning-based nonlinear autoregressive network with exogenous inputs (NARX) Neural Network (NN) in order to remove the artifacts from the ECG signals. By exploiting the adaptive filter, after identifying the artifact signal, the recognized signal is subtracted from the main signal which is consists of the ECG signal and the artefacts using an adaptive subtraction process. Hence, the uncontaminated signal is attained, which is exploited for effectual diagnosis procedures and the analysis is carried out to show the efficiency of the developed technique, which reveals that the proposed method attained an maximum Signal-to-noise ratio (SNR) and least error.

Keywords: ECG artefact, signals, NARX, NN, SNR

Nomenclature

Abbreviations	Descriptions
APSM	Adaptive Periodic Segment Matrix
mVMD	modified Variational Mode Decomposition
ECG	Electrocardiogram
IMFs	Intrinsic Mode Functions
CVD	Cardiovascular
SVD	Singular Value Decomposition
DCT	Discrete cosine transform
DTCWT	Dual tree complex wavelet transform
CEEMD	Complete Ensemble Empirical Mode Decomposition
EMD	Empirical mode decomposition
FIR	Finite Impulse Response
BLIMFs	Band Limited Intrinsic Mode Functions

1. Introduction

ECG is considered as the significant biomedical signals to indicate the health of the human. It presents information regarding the heart's functional circumstances. The heart rates have the ability to indicate the environment of the human body as well as its performance in cases. Generally, the ECG signals are distorted using the artifacts which affect the health diagnosis outcomes and monitoring. Hence, signal separation and de-noising are considered important procedures in engineering fields [1].

The automatic analysis technique plays a significant role in attaining rapid and accurate CVD disease. For decades, CVD is considered as one of the human life threats, and millions of persons die because of delayed treatment and diagnosis. ECG signal exhibits the graphical representation of the cardiovascular movement as well as its application for the detection of diverse heart abnormalities and

https://doi.org/10.46253/jcmps.v4i3.a3

disease [2]. ECG has new characteristics of morphological P-QRS-T and on verifying the deviation in these features a lot of cardiac diseases can be identified. Nevertheless, the attendance of diverse noises has a finely tuned influence on precise feature extraction in ECG signals.

The performance of signal de-noising is to drives out the noise from the unclean signal without altering its characteristics. In some works, thresholding technique on the basis of the non-linear multiresolution analysis is performed which is a feasible technique to attain denoised signal by calculating the value of the threshold and evaluating every coefficient over a threshold to recuperate the coefficients which are higher than a noise. The threshold technique is recognized for its maximum-speed calculation and reduced memory storage [3].

In current decades, for ECG signals, numerous noise removal techniques have been developed that were extensively used for numerous applications namely computer-aided diagnosis, fetal monitoring of ECG signal [11] and [12]. They importantly involve the subsequent kinds such as digital filtering, for instance, the FIR filter and the infinite impulse response filter. For a certain frequency range, digital filters are extensively exploited for the removal of the noise due to the ease and effectuality; however, they cannot cope up with the frequency overlapping scenario. Morphological filters consist of the opening and closing operators for the morphological are frequently exploited to smooth the ECG signal. Although, it is non-durable to ascertain the shape and the size, it is very easy to remove the noise with equivalent size and shape to the structuring element is efficient. Then, the wavelet-based denoising such as wavelet transform is the widely effective tool for the denoising of ECG as the signal can be decomposed into modules comprising both frequency and time information at diverse scales. By using the threshold, the wavelet-based denoising experiments to modules associated with the noises. Nevertheless, few types of noises for instance motion artifact does not possess clear frequency patterns and might subsist in diverse modules. In this scenario, it is very difficult to calculate the level of the noise as well as ascertain suitable thresholds [4]. EMD based denoising named EMD represents a technique in which signal is decomposed into a series of IMFs. It majorly comprises noise are eradicated for ECG denoising and residual IMFs are the summation of the remodel of the uncontaminated signal. As same as the wavelet transform, the noise is decomposed by the EMD with variable frequency and morphology into multiple IMFs. Additionally, in an empirical manner decomposition levels are ascertained. In template-based denoising, in ECG signals the heartbeats generally possess the same shape as well as an uncontaminated heartbeat template can be calculated by averaging noisy modules. Subsequently, diverse kinds of signal remodeled based upon the template and ultimately concatenated to attain the uncontaminated signal.

The main contribution of this paper is to develop a new model to train the NARX NN which is on the basis of the Improved Chicken Swarm Optimization algorithm with LM -based method. Moreover, the main objective of this work is the artifact removal that presents in the ECG signal for the effectual diagnosis of heart disease and other associated issues. In order to tune the weights, the adaptive filter exploits the NARX NN which exploits the proposed technique. On the basis of the weights, the adopted model trains the network effectually which corresponds to the minimum error value. Therefore, the proposed model for the artefact removal represents an effectual procedure in eradicating the noise signals, like EMG, ECG, and EOG.

2. Literature Review

In 2020, Xieqi Chen et al [1] developed a new APSM on the basis of the SVD from EMG artefacts to extract the uncontaminated ECG signals. At first, a periodic module calculation technique was developed by attaining RR intervals constraint and an average periodic length through a wrapping measured signal spectrum. Then, aforesaid techniques were used to detect the ECG signal positions and the R wave peaks. Subsequently, the R wave peaks were exploited to form the APSM with rank one and the computed RR intervals restraint, after that SVD was processed in this matrix. Using the value of the maximal singular the ECG signal of restructured was attained.

In 2021, Xiaoyun Xie et al [2], developed a multi-stage ECG denoising structure, which focused on motion artifact detection on the basis of domain knowledge. Here, initially, using the noise-adaptive thresholding, motion artifact candidates were positioned. Subsequently, to identify the actual motion artefacts, multiple metrics integrated with decision rules were exploited, and using the morphological filtering and local scaling they were suppressed. To remove baseline wander and high-frequency noise, the CEEMD and wavelet transform were exploited.

In 2019, Chinmayee Dora and Pradyut Kumar Biswal [3], developed an ECG artifact improvement technique in the non-presence of coherent ECG for automatic diagnosis or analysis of the attained impure single-channel EEG signal. An improved and enhanced version for single decomposition was exploited by the developed model named mVMD to attain BLIMFs from the EEG epoch. The mVMD was obtained and it was aided while the signal comprises the properties which were correlated. Moreover, the correlation was exploited between the attained mode functions; the ECG artefacts modules were recognized.

In 2019, Fan Xiong et al [4], proposed the spectral energy alters at the time of the input process of motion artifacts, a DCT LMS adaptive cancellation technique (DCT-LMS) which aims to eradicate the motion artifacts from the ECG.

In 2021, Navdeep Prashar et al [5], presented a complete description of the choice effect of the threshold algorithm, threshold value, and distribution function to estimate the performance of the ECG signal denoising using the DTCWT. Here, eight diverse sets of threshold value selection rules along with six different threshold functions were experimented and calculated on the MIT-BIH arrhythmia database.

3. ECG Artefact removal using the Developed Model

A novel ICSO LM-based NARX NN is proposed for the removal of the artefacts in ECG signals. This work presents a detailed analysis of the adopted model for the removal of artefacr from the ECG signals, which receives huge attention and also possesses several benefits such as effectual cardiac disease diagnosis and aids the doctors to take effectual metrics.

3.1 Artefacts removal from the ECG signals

Generally, ECG is represented as the electrical activity record of the hearing at the time of the recording procedure. Here, the artefacts are involved with the ECG signals because of the intrusion effects of the other signals namely EMG, EEG, and EOG which might present adverse effects on the cardiac diagnosis-associated diseases. The issues that occurred by the artefacts are overcome by performing the adaptive noise cancellation scheme in an effective manner [6] for the removal of the artefacts like EOG, EEG, and EMG signals. Hence, the adaptive noise cancellation method is exploited in order free from the artefacts, and the cancellation model needs two inputs. Here, one input obtains from the ECG signal sources, and the other input is obtained from the artefacts. Hence, the main input signal is the integration of the signals which is attained from the ECG signals that are the uncontaminated signal, and the intrusion signal which is attained by passing the artefact via the unrecognized nonlinear dynamics. Hence, the main signal is denoted as below:

$$B(i) = C(i) + I(i) \tag{1}$$

$C(i)$ indicates clean ECG signal, $B(i)$ indicates the main input signal and $I(i)$ indicates interference which is produced exploiting the unidentified nonlinear dynamics or else the signal attained by the noise source.

In order to generate the filtered output, the noise signal is fed to an adaptive filter that is the same as the interference signal produced, as an outcome of the nonlinear dynamics. Hence, the noise cancellation is carried out which extracts the uncontaminated signal via the filtered output subtraction from the main input signal. Hence, by exploiting the noise cancellation scheme the clean signal is extracted and it is stated as below:

$$C^*(i) = B(i) - A(i) \tag{2}$$

whereas, $B(i)$ denotes the main input signal, $C^*(i)$ denotes the clean signal attained consequently by the adaptive noise cancelation, and $A(i)$ denotes the adaptive filtered output. Fig. 1 demonstrates the developed noise cancelation scheme.

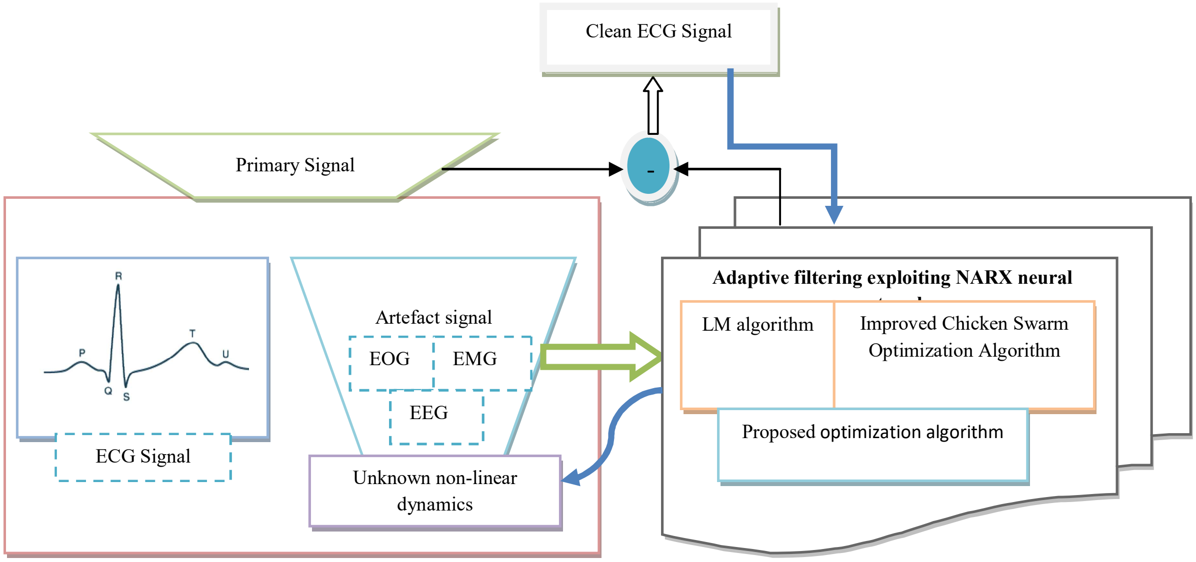


Fig. 1: *ECG artefact removal*

3.2 Enhanced adaptive filtering using NARX NN model

In this section, by exploiting the NARX NN model [10], the developed model for the removal of artefact from the ECG signal is described. One of the major contributions of the NARX NN is to forecast the artefact that is available in the ECG signal so that the clean ECG signal is produced for the ideal diagnosis. Here, the artefact is the input for the NN, and to predict the signal the delays are exploited.

In the developed learning model, an optimized solution is produced by means of three weights, such as the exogenous input vector weights, the regressed output vector weights, and exogenous output vector weights. To produce an optimized weight these three weights are integrated so that the optimized output trains the NARX NN in the removal of the artefacts and the solution vector size is based upon the number of hidden neurons available in the network. Consider, the regressed output weights are indicated as $\{R_1, R_2, ..., R_{d_2}\}$, the exogenous input vector weight as $\{L_1, L_2, ..., L_{d_1}\}$, and the exogenous output vector as, $\{O_1, O_2, ..., O_{d_1}\}$. Subsequently, by exploiting the LM algorithm the solution is produced and the proposed optimization technique is indicated as $\{X^{l1}, X^{l2}, ..., X^{lf}\}$ and $\{X^{d1}, X^{d2}, ..., X^{df}\}$ correspondingly. Hence, the developed optimization algorithm produced the optimal weights which are stated as a $\{X^{z1}, X^{z2}, ..., X^{zf}\}$.

3.3 NARX NN model

NARX NN [7] is a recurrent NN that is exploited for the modeling and analysis of the non-linear time series and possesses numerous advantages while comparing with the conventional prediction models. In the developed model of noise cancellation, the NARX network has an effectual learning rate, the learning method exploited is the ICSO and LM algorithm [8].

The NARX NN is the gather of the recurrent loop, multilayer fed forward network and the time delay. It possesses three layers such as input layer, the hidden layer, and the output layer. To the tapped delays the network is feded, both in the input layer and the output layer as well as the feedback flows in a single direction. The input and hidden layer are followed by the feedback and present the output in the output layer. In the input layer, there are three information vectors such as exogenous input, delayed exogenous input vector, delayed regressed output vector. NARX NN output is stated as below:

$$N(l+1) = F[N(l), N(l-1), N(l-2)..., N(l-d_1); S(l), S(l-1), S(l-2)..., S(l-d_2)] \quad (3)$$

In eq. (3), $N(l-1), N(l-2)..., N(l-d_1)$ represents delayed regressed output vector, $N(l)$ indicates exogenous input vector, and $S(l-1), S(l-2)..., S(l-d_2)$ denotes the delayed exogenous input vectors. At the initial stage, the NARX network function, the weights are allotted among the input layer and the hidden layer as well as the hidden layer and the regressed output vector.

4. Proposed ICSO Model

The conventional CSO optimizer is a group intelligent optimizer that imitates the hierarchical system and the chicken swarm foraging behavior. The optimizer partitions the chickens into flocks. Every group comprises a cock, various hens and some chicks [9].

The Conventional CSO optimizer possesses reduced global search as well as local search abilities while cope up with additional complex issues [9]. This paper enhances the CSO optimizer and makes stronger the global and local search abilities of the CSO optimizer in order to resolve this issue. In this conventional algorithm, the cock superiors the collect and it possess the effectuality foraging capability. In the group, in a local optimum while the cock is captured and reasons the complete group to fall into local optimum. To strengthen the local search capability of cock particles the cosine inertia weight is developed. In the position of chick particle, the optimal particle learning part is developed to update the formulation to enlarge the search range of chick particles. The group search range is slowly contracting during the afterward phase of iteration. To improve the population diversity the Cauchy mutation operator is developed in the later phase of iteration.

Subsequent to the cosine inertia weight is introduced; the location update formulation of i^{th} cock particle is stated as below:

$$Z_{i,j}^{t+1} = Cip * Z_{i,j}^{t} + Z_{i,j}^{t} * rn\left(0,\sigma^2\right) \tag{4}$$

$$Cip = Cip_{min} + \left(Cip_{max} - Cip_{min}\right) * \cos\left(\pi * \frac{t}{T}\right) \tag{5}$$

Where, Cip indicates Cosine Interia weight, $Cip_{min} = 0.3, Cip_{max} = 0.8$

Initially, the cock particles globally search and subsequently locally search during the complete iteration procedure. Using cosine inertia weight, the global and local search capability of cock particles is enhanced. Subsequent to the enhancement, the location update formulation of the i^{th} chick is stated as below:

$$Z_{i,j}^{t+1} = Z_{i,j}^{t} + GL(i) * \left(Z_{m,j}^{t} - Z_{i,j}^{t}\right) + BL(i) * \left(Z_{besr,j}^{t} - Z_{i,j}^{t}\right) \tag{6}$$

$$BL(i) = \exp(S_{best} - S_i) \tag{7}$$

where S_{best} indicates the best particle in the flock; $BL(i)$ indicates the learning coefficient.

From the hen particles, the chick particles not only learn around them but however also learn from the optimal particle in the group. Then population search phase, the group is highly to fall into the local best value. Hence, the current iteration number goes beyond 90% of the total count of iterations as well as the Cauchy mutation operation is developed. Then the computation procedure of the Cauchy mutation operator is stated as below:

$$z^* = z + \lambda * cauchy(t) \tag{8}$$

whereas z indicates the pre-mutation particle; $cauchy(t)$ indicates the Cauchy distribution random variable; z^* indicates the mutated particle; λ controls the different intensity of the Cauchy mutation operator.

5. Result and Discussion

The developed technique result was briefly explained to detail the higher performance of the developed modeled over the conventional models such as DLM Dragonfly-LM, Particle Swarm Optimization (PSO-LM), Grey Wolf Optimization (GWO-LM), and Genetic Algorithm (GA-LM) in this section.

Fig 2 (a) demonstrates the performance analysis of the proposed and conventional models regarding the SNR (dB) in the attendance of the ECG signal. Here, the proposed method attains maximum SNR than the conventional models. Here, the proposed method is 12% better than the PSO-LM, 11% better than the GWO-LM, 10% better than the GA-LM interms of SNR. Fig 2 (b) exhibits the performance analysis of the proposed and conventional models regarding the MSE in the attendance of the ECG signal. Moreover, the proposed method is 22% better than the PSO-LM, 21% better than the GWO-LM, 18% better than the GA-LM interms of MSE. Here, the proposed method attains a minimum MSE than the conventional models. Fig 2 (c) depicts the performance analysis of the proposed and conventional models regarding the RMSE in the attendance of the ECG signal. Moreover, the proposed method is 22% better than the PSO-LM, 15% better than the GWO-LM, 17% better than the GA-LM interms of RMSE. Here, the proposed method attains a minimum RMSE than the conventional models.

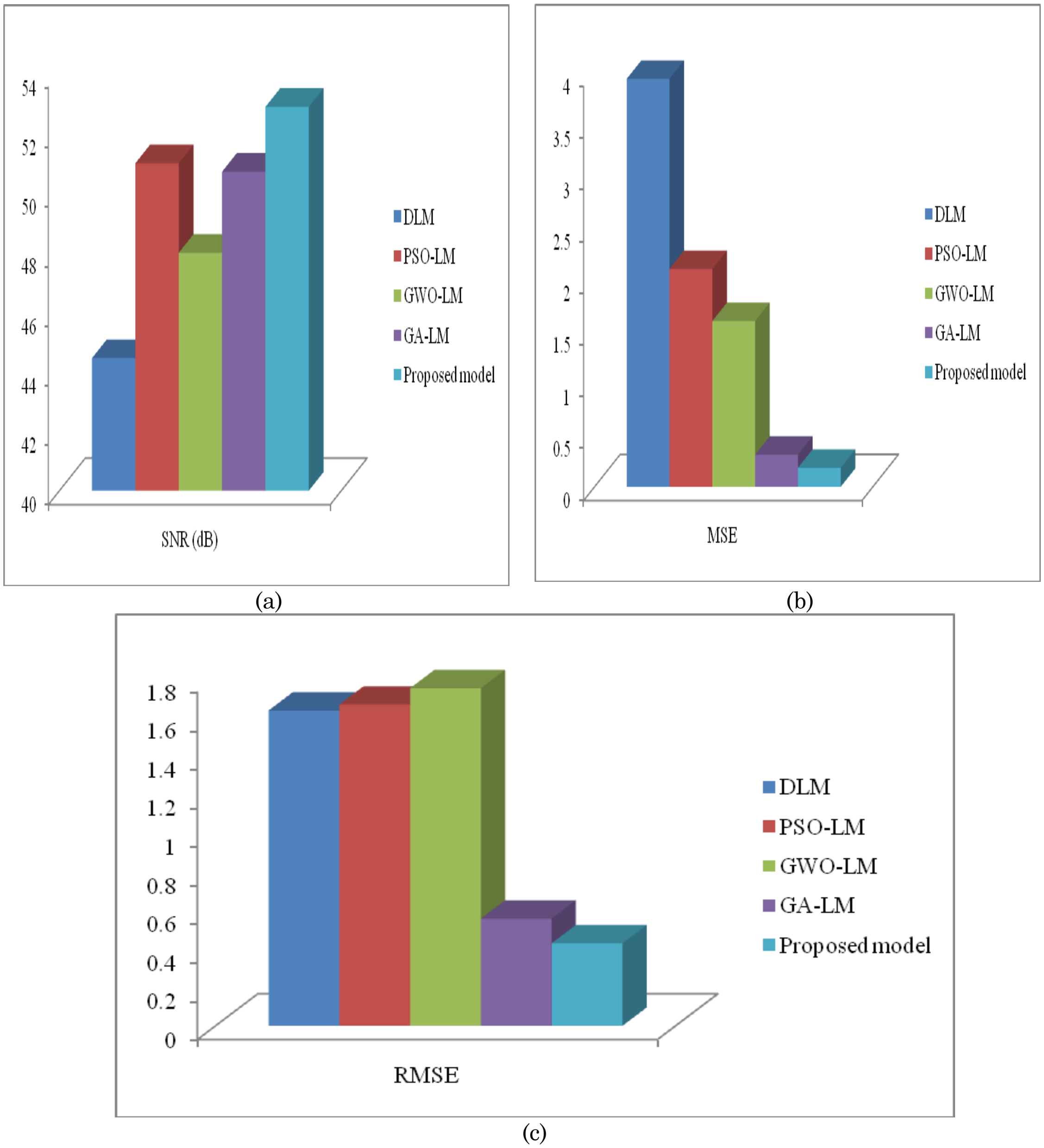


Fig 2. *Performance analysis of the proposed and conventional models (a) SNR (b) MSE (c) RMSE*

6. Conclusion

From ECG signals the noise elimination was a challenging issue as noise causes serious problems in the inspection of the signal and its analysis. In this work, the removal of artifact was presented by exploiting the proposed optimization model based on NARX NN. Here, the adopted model exploits both the ICSO algorithm and the LM learning approach to train the NARX NN. Here, an easy subtraction technique was exploited to remove the artifact from the ECG signal so that the ECG signals attained were uncontaminated which was appropriate to diagnose the heart associated diseases. By exploiting the ICSO-based NARX NN model, the adaptive tuning of artifact removal was performed so that the developed model was considered as an effectual method for the removal of the artefact. Moreover, the artefact signals were exploited for the experimentation namely EEG, EOG, and EMG which revealed that the developed model was effectual while comparing with the conventional models.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

References

[1] Xieqi ChenJianhui LinLiu He,"A novel method based on Adaptive Periodic Segment Matrix and Singular Value Decomposition for removing EMG artifact in ECG signal", Biomedical Signal Processing and Control, 29 July 2020.

[2] Xiaoyun XieHui LiuYinglong Wang,"A multi-stage denoising framework for ambulatory ECG signal based on domain knowledge and motion artifact detection", Future Generation Computer Systems, 31 October 2020

[3] Chinmayee DoraPradyut Kumar Biswal," Correlation-based ECG Artifact Correction from Single Channel EEG using Modified Variational Mode Decomposition", Computer Methods and Programs in Biomedicine,28 September 2019.

[4] Fan XiongDongyi ChenShumei Dai"Cancellation of motion artifacts in ambulatory ECG signals using TD-LMS adaptive filtering techniques", Journal of Visual Communication and Image Representation,15 December 2018.

[5] Navdeep PrasharMeenakshi SoodShruti Jain,"Design and implementation of a robust noise removal system in ECG signals using dual-tree complex wavelet transform", Biomedical Signal Processing and Control14, September 2020.

[6] [24] Aysa Jafarifarmand, Mohammad Ali Badamchizadeh, "Artifacts removal in EEG signal using a new neural network enhanced adaptive filter", Neurocomputing, vol.103, pp.222-231,1 March 2013.

[7] [22] José Maria P. Menezes Jr and Guilherme A. Barreto, "Long-term time series prediction with the NARX network: An empirical evaluation", Neurocomputing, vol.71, no.16–18, pp.3335-3343, October 2008.

[8] JIAO JianLIN JunLU Hao,"Inversion of Neural Network Rayleigh Wave Dispersion Based on LM Algorithm", Procedia Engineering, 2011.

[9] Mahendra Bhatu GawaliSwapnali Sunil Gawali,"Optimized skill knowledge transfer model using hybrid Chicken Swarm plus Deer Hunting Optimization for human to robot ", Knowledge-Based Systems1, 7 March 2021.

[10] Vinolin V and S Vinusha,"Enhancement in Biodiesel Blend with the Aid of Neural Network and SAPSO",Journal of Computational Mechanics, Power System and Control, vol. 1, no. 1, October 2018,

[11] K.Srinivas"Prediction of E-Learning Efficiency by Deep Learning in EKhool Online Portal Networks", Multimedia Research, vol. 3, no. 4, October 2020

[12] Arvind Madhukar Jagtap,"Developing Deep Neural Network for Learner Performance Prediction in EKhool Online Learning Platform", Multimedia Research, vol. 3, no. 4, October 2020.