IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, April 2025
Impact Factor: 7.67

Intelligent EEG Signal Processing: A Design of NN-based Adaptive Filtering for Artifacts Eradication

Vishal Singh Chouhan and Dr Navdeep Kaur Saluja
Department of CSE
Eklavya University, Damoh, India
visshal.chouhan@gmail.com and navdeep.saluja2000@gmail.com

Abstract: *Electroencephalogram (EEG) signals are widely used for brain activity analysis, but the presence of motion artifacts can significantly degrade disease diagnosis results. This paper proposes a novel approach to eradicate detected motion artifacts using a neural network (NN) based adaptive filter. The study considers EOG and EMG based motion artifacts databases. The performance of theintelligent adaptive NN filter is evaluated using a back propagation based NN as a gradient descent problem. Parametric evaluation of various EEG data for artifacts removal methods is also proposed. The study suggests using NN-based de-noising to increase signal intensity after artifacts elimination. SNR and RMSE calculations are employed to evaluate the performance of NN-based adaptive filtering algorithms. The proposed NN filter is capable of accurately learning the data and eliminating the impact of EOG amplitude peaks. Quantitative results demonstrate that the proposed method offers significant improvement in PSNR of 6 dBand PSD performance over existing approaches, with PSD improvement nearly 0.15 over ICA and 2.4 times more than CCA. The study concludes that the proposed NN-based filter is an effective approach for removing motion artifacts from EEG signals while preserving the underlying brain activity, making it suitable for accurate disease diagnosis.*

Keywords: Electroencephalogram (EEG), Motion Artifacts, Eye blink, Muscular artifacts. Adaptive NN Filter, PSNR

I. INTRODUCTION

Electroencephalography (EEG) is a crucial tool in neuroscience and clinical practice for monitoring brain activity. However, EEG signals are often contaminated by various artifacts, such as eye movements, muscle activity, and electrical interference, which can significantly impair signal quality and interpretation. To address this challenge, intelligent EEG signal processing techniques have emerged as a promising solution. This paper presents a novel approach to artifacts eradication in EEG signals using a neural network-based adaptive filtering method. By leveraging the power of machine learning and signal processing, this technique aims to automatically identify and remove artifacts while preserving the underlying brain activity information. The proposed method offers several advantages over traditional filtering approaches, including improved adaptability to different artifacts types and enhanced preservation of clinically relevant EEG features. The research sets the stage for a detailed exploration of the design, implementation, and evaluation of the neural network-based adaptive filtering system for intelligent EEG signal processing.The NN - based adaptive filtering techniques have emerged as powerful tools for artifacts removal in EEG signal processing. These methods combine the strengths of machine learning and signal processing to effectively eliminate various types of artifacts while preserving the underlying neural activity. Several studies have demonstrated the efficacy of adaptive filtering approaches for EEG artifacts removal. For instance, a recurrent neural network (RNN) based technique combining an adaptive noise cancellation and adaptive signal enhancement has been proposed for real-time removal of ocular artifacts from EEG (Selvan & Srinivasan, 1999 [1]).

DOI: 10.48175/568

This method employs a real-time recurrent learning algorithm that converges quickly to a lower mean squared error, making it suitable for real-time processing. Another method utilizes a recurrent neural network as an adaptive noise canceller to model and remove electro-oculogram (EOG) interference from EEG signals (Erfanian & Mahmoudi, 2005 [2]). An intelligent approach achieved significant improvement in signal-to-noise ratio, up to 27 dB on average. Interestingly, some methods do not require additional EOG recordings, which can be inconvenient for subjects. The spatial constraint independent component analysis based recursive least squares (SCICA-RLS) method uses ICA to decompose EEG channels and identify ocular components, which are then used as reference signals for adaptive filtering (Yang et al., 2015 [3]). This approach led to higher classification accuracies and faster computation times compared to standard ICA. In conclusion, neural network-based adaptive filtering techniques offer effective solutions for real-time EEG artifacts removal. These methods demonstrate improved performance in terms of artifacts reduction, preservation of relevant brain activity, and computational efficiency, making them valuable tools for various EEG-based applications, including brain-computer interfaces and clinical diagnostics.

Interestingly, some research has explored hybrid approaches that combine multiple techniques. For example, a method integrating nonlinear adaptive filtering and signal decomposition was developed for motion artifacts removal in photo-plethysmography signals, achieving improved heart rate estimation accuracy (Ye, Y., Zhang et al., 2016 [4]). This hybrid approach demonstrates the potential benefits of combining different artifact removal strategies. In conclusion, neural network-based adaptive filtering techniques offer promising solutions for intelligent EEG signal processing and artifacts eradication. These methods can effectively handle various types of artifacts, including ocular and motion-related disturbances, while preserving the underlying neural information. The ability to perform real-time processing makes these approaches particularly valuable for brain-computer interface applications and other scenarios requiring online artifacts removal.

Number of patients during COVID-19 had experience brain-related problems, necessitating the collection of massive amounts of EEG data. This encourages the development and testing of filter applications for the processing of EEG signals. If artifacts are available in the EEG data then it is a challenge to eliminate these artefacts from EEG signals, thus numerous artefact reduction techniques have been developed. The filter design is the at most essential block of almost all signal processing applications. The adaptive filters are widely used for EEG artifacts eradication such as LMS filter (P. Sharma 2023 [5]), the RLS adaptive filter (Behera et al 2023 [6]). But it is observed that most of the filters smooth every EEG data without checking for presence of artifacts this may significantly over smooth true EEG data. Therefore this paper proposed to solveartifacts eradication problem using the design of efficient adaptive NN based filter. It is observed that in the presence of muscular and eye motions during EEG signal acquisition time may cause motion artifacts.

Because adaptive neural filters make use of neural networks' (NN) ability to learn from data and adapt to changing conditions, they are particularly helpful for filtering complex and non-stationary signals like EEG.The main advantage of adaptive filter is that it is capable of learn the features and nature of EEG based on the input desired EEG signals. Motion artefacts are considered for the research, namely optical eye blinks (EOG) as well as muscular artefacts (MMG). The primary goal is to remove artefacts related to high peak eye blinks. Thus, the research proposed to use NN based de-noising to boost the signal intensity once the artefacts were removed. SNR and RMSE parameters are used for evaluating the performance of NN based adaptive filtering techniques.

Reasons of Artifacts: The main reasons of Artifacts presence in EEG signals are illustrated in the Figure 1. The main causes of EEG artifacts are eye movements and muscular motions. Additionally electrode and wire movements may also cause error.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 5, Issue 5, April 2025 Impact Factor: 7.67

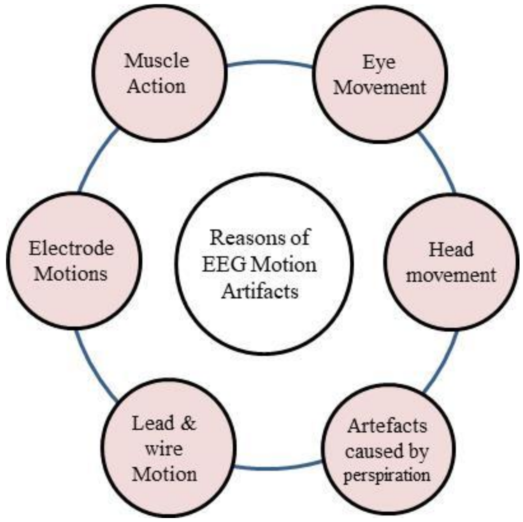


Figure 1 Reasons of the EEG Artifacts

Problems: Nearly all EEG signals that have been obtained or signals that are sensitive to head movement during the EEG acquisition are responsive to the addition of Gaussian noise to the real signal patterns. The true data from these signals can be reproduced by designing an effective digital filter. The most important issue is to maintain the shape of the ECG data. Most of previous method may tend to over smoothen the data and may casus to disturbed the true EEG nature. The impact of the motion artifacts are illustrated in Figure 2. It can be observed that eye blinks are impulsive and have higher peaks. While muscular motion may expand across the EEG signal to cause artifacts and significantly change the nature of true EEG. .

Thus faltering efficiently is essential task and qualitative evaluation is required. It is also observed that most of the previous methods are unable to minimize the high peaks eye blink artifacts even after filtering. This paper addressed the detection of motion artifacts by proposed design of NN adaptive filter.

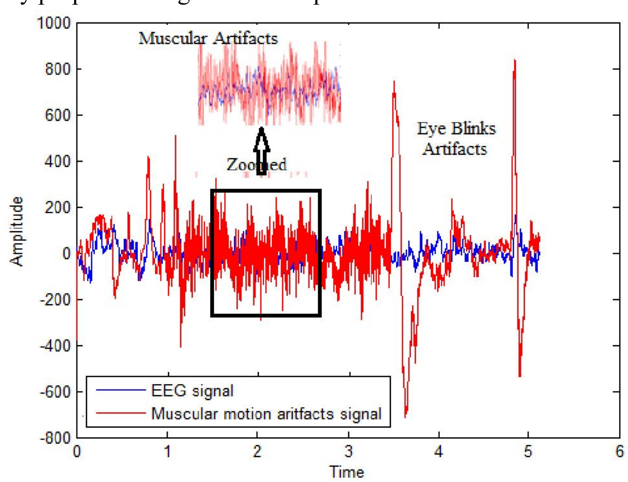


Figure2 representation of different EEG artifacts and there impacts

Benefits of NN Filter

When compared to conventional filtering techniques, an NN filters provide the following benefits for eliminating artefacts from EEG signals:

Enhanced Accuracy**:** EEG signals including artefacts have complicated properties that neural networks can learn. This minimises the effect on the basic brain activity and also enables them to modify their filtering behaviour to particularly

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429 Volume 5, Issue 5, April 2025 Impact Factor: 7.67

target as well as remove artefacts. Certain artefacts may be difficult for traditional filters to discern, particularly if they have features similar to true EEG waves.

Non-linear Artefact Elimination: The features of EEG artefacts may exhibit non-linearity, i.e., they may alter with time. Since traditional filters are usually linear, they might not be able to get rid of these kinds of artefacts. On the other hand, non-linear interactions are handled by NN, which can modify their filtering as necessary.EEG data can be tainted by a range of sounds, including eye movement and muscle activity. Adaptive neural filters, which may effectively achieve the capability to filter each of these artefacts while keeping the underlying brain signals, can be used to boost the accuracy of the EEG data

Decreased Signal Distortion: Conventional filtering methods may cause both the artefacts and the real EEG signal to be distorted. By training neural networks to become more selective when filtering, the effect on the intended brain activity can be reduced.

Learning through Multiple Data Sources**:** Big datasets for EEG recordings with a variety of artefacts can be used to train neural networks. As a result, they can eventually become more effective by learning to apply existing filtering skills to types of artefacts they haven't yet seen.

.In rest of this paper first various related works are reviewed in section 2. The multi-mode decomposition machine learning (ML) methods for pre-processing are described in the section 3. The sequential proposed NN filter methodology for EEG artifacts eradication is presented in section 4. The results of the EEG artifacts removal along with mode decompositions are illustrated in the section5 followed by the conclusions and future scopes.

II. RELATED WORKS

This section reviewed various related works to EEG processing. P. Sharma et al. [5]stated use of EEG, for the purpose of determining diseases affecting the neurological system. An EEG is a specialist diagnostic device used to measure the electrical discharge in the brain. From EEG recordings, abnormalities of the human brain and its reactions to inputs can be inferred. Recordings of EEG may become distorted as a result of artefacts, or unwanted signals. It is difficult to interpret the EEG because these variations create bursts that might be misinterpreted as brain patterns, and since almost all biological signals have time-varying features. Consequently, noise and undesirable signals must be eliminated from the EEG in order to ensure a precise examination and interpretation. Behera, Sandhyalati et al. [6]has goal to study eliminating ventricular noise from the electrical activity of the brain using an adjusted balanced RLS filter. An improved weighted RLS technique is used to quantify and remove cardiac artefact from the EEG data. Knowledge Quality (IQ), mean square error (MSE), Increase in Signal to Artefact Ratio (GSAR), Signal to Noise Relationship (SNR), and INPS are used as verification metrics. The section that follows compares the suggested method's effectiveness with previous approaches such as the independent component analysis (ICA), technique and the least squares notch filter.

Chen, X., et al [7] have proposed a unique method, called EEMD-CCA, for removing muscular artefacts from EEG data through the use of the ensemble empirical mode decomposition (the EEMD) and canonical correlational analysis (CCA). This strategy can effectively use inter-channel data. We evaluated the method on three different data sets: real-world, semi-realistic, and artificial. The method fared better than cutting-edge methods like EEMD-ICA, CCA, and standalone component analysis. K. T.Sweeney et al [8]have proposed a study presenting a revolutionary artefact removal approach. Single-channel observations can be used to apply the ensemble empirical mode decomposition with canonical correlation analysis (EEMD-CCA) approach. The single-channel output is first broken down into a dimensional signal using the EEMD approach. Second-order characteristics can be used in conjunction with the CCA approach to separate the artefact parts from the core signal. Employing both electroencephalographic and near-infrared spectroscopy data, the novel method is compared against the existing wavelet blurring and EEMD-ICA approaches and is demonstrated to yield much better results.

Benning, K et al [9] have proposed ICA as effectively used in recent times to eliminate artefacts and noise from pictures acquired by Three-dimensional in nature Divided Light Identification (3D-PLI) at the micro scale (64 µµm). Here, we provide an autonomous grey matter area blurring process that enables the modest computing effort to use the ICA to micro pictures as well. In addition to automatically segmenting portions of the grey matter, we also used the noise reduction process to several 3D-PLI pictures of the brain sections of a vervet monkeys and a rat. D. Pancholi, et al [10]has a goal to eliminate motion artefacts from EEG data that are recorded for robot movement and orientation systems for control. The paper initially outlines the robotics applications of the BCI system. The effectiveness of many artefact removal techniques, including ICA, EEMD-CCA, and EEMD-CCA-DWT, is compared in this paper. For a robotic artefact removal usage, the different outcomes of the Intrinsic Modal Function (IMFs) deconstructed from these techniques are assessed and contrasted. In accordance with quantitative studies, it is discovered that CCA-based procedures are both effective and quicker than alternative approaches.

J. Gao, et al [11] has proposed a novel method is suggested to further evaluate enhance, and shorten the filter calculation time. This novel CCA technique is based on the principle of Gaussian elimination, which is intended to remove motion artefacts from EEG signals and is used to calculate coefficients of correlation using backslash operations. The elimination of Gaussian parameters reduces the computational cost of the CCA technique by solving linear equations to determine Eigen ratings. Combining EEMD-CCA and wave change, this innovative suggested technique is evaluated against existing artefact removal strategies. Data from both simulated and actual EEG signals are used to assess the effectiveness.

Roy Vandana et al. [12] has proposed a method is suggested to further evaluate enhance, and shorten the filter calculation time. This novel CCA technique is based on the technique of Gaussian elimination (GE), which is intended to remove motion artefacts from EEG signals and is used to calculate correlation values using backslash operations. The elimination of Gaussian reduces the computational cost of the CCA technique by solving linear equations to determine Eigen values. Applying EEMD-GE-CCA and wave change, this innovative suggested method is evaluated against existing artefact removal strategies. Data from both simulated and actual EEG signals are used to assess the performance.

Zhang, C. et al [13] have presented an automated approach for removing EEG artefacts from a single channel of EEG recordings. The software successfully lowers the following kinds of artefacts: ocular artefact (OA), transmission-line/harmonic-wave artefact (TA/HA), and muscular artefact (MA). The efficacy of the suggested approach is confirmed using genuine EEG information from the CHB-MIT dataset as well as noisy EEG signals that are created. The results of this study demonstrate that the suggested approach successfully eliminates motion artefact in addition to OA, MA, and TA/HA during a single-channel EEG record. Hemant Amhia et al. [14]presented a synthetic intelligence-based method for QRS peak identification and ECG data categorization is proposed. It is suggested to create a lower order IIR filter to low pass smoother the electrocardiogram (ECG) data. To create a reduced order filtering, the filter parameter has to be optimised using the min-max method. The major focus of this research article is on removing baseline noise and power line disruptions from the electrocardiogram (ECG) signal. Vyas, P. K. et al. [15]suggested that multidimensional photos taken at various sessions will reveal changes in land cover, which determines the importance of change-detection algorithms. Effective detection of changes (CD) has not yet been discovered based on the prior works. Based on several current methodologies, the Improved Reverse propagation Neural Networks (EBPNN) methodology for CD is applied to improve the precision. This technique uses an Adaptive Minimum Filter (AMF) to eliminate the noise found in photos taken via satellite imagery.

Prerna Kumari et al. [16]had a goal to setup de-noising techniques for digital hearing aids and voice augmentation. Efficiency is assessed and a variety of approaches based on FIR & IIR filter layouts are offered. It has been noted that the considerable waveform decrease that occurs during noise reduction makes waveform reshaping techniques difficult to use for immediate voice recordings. In order to improve amplitude, this paper prepares the adaptive scaling approach. The paper's main objective is to develop an effective process for digital hearing devices. Maddirala, A.K et al. [17]have studied a novel framework to eliminate eye blink artefact without altering the underlying EEG data by combining the single spectrum assessment (SSA) approach with the unsupervised artificial intelligence technique (k-means). The work's innovation is in how the uncontrolled artificial intelligence technique and the time-domain properties of the electroencephalogram (EEG) signal were used to extract the eye-blink artefact. To get the corrected EEG data, the recovered eye-blink artefact is handled further using the SSA approach and then removed from the polluted one-channel EEG signal. Findings using both simulated and actual EEG data show how much better the suggested approach is than the current ones.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, April 2025
Impact Factor: 7.67

L. Wang, et al. [188]presented, a unique EMD-ICA eliminating approach is presented, in which each mode's probabilistic density function (pdf) and the input data are compared using the hausdorff distances (HD) metric to choose significant modes. Then, multiple vectors for input are constructed using the first layer fundamental modality functional (IMF). These multivariate vector inputs are sent into the ICA in order to provide aliasing-assisted filtration of each IMF layer. A computer simulation was performed to assess the efficacy of the suggested approach. Test and modelling findings demonstrate its overall superiority than other conventional blurring techniques. X. Chen et al. [19]propose a unique method, called EEMD-CCA, for removing muscular artefacts from EEG data through the use of ensemble empirical mode decomposition (EEMD) with classical correlational analysis (CCA). This strategy can effectively use inter-channel data. We evaluated the method on three different data sets: real-world, semi-realistic, and generated. The method fared better than cutting-edge methods like EEMD-ICA, CCA, and autonomous component analysis. The significance ($p<0.01$) in (semi)-simulated investigations is shown by statistical analysis.

S. Shukla et al. [20]stated that workable biological signal is required for the diagnosis of human health. Therefore, one of the most important steps is to remove artefacts from the physiologic signal. An input one-channel EEG signal is transformed into a multi-channel EEG signal using an ensemble empirical mode decomposition (EEMD) technique. The Canonical correlation analysis (CCA) technique is used to enhance the processing of this multi-channel EEG input. The DWT (discrete wavelet transforms) is then used to eliminate any residual artifact-related unpredictability from the signal. Using effectiveness indices such as Del Signals to Noise Rate (DSNR), Lambda, and Root Mean Square Error (RMSE), and Power Spectrum Distribution (PSD) enhancement, this strategy is tested and compared to existing artefact removal methods.

Mahmud, S et al. [21] have proposed a unique 1D convolutional neural network, also known as the CNN, for signal reconstructing for EEG motion artefact reduction, which is named the multi-layer multi-resolution radially pooling (MLMRS) networks. Ten other 1D CNN models were examined to see how well the suggested model performed in terms of eliminating motion artefacts from movement-contaminated single-channel EEG signals: FPN, LinkNet, UNet, UNet+, UNetPP, UNet3+, AttentionUNet,DenseInceptionUNet, MultiRes-UNet,and AttentionUNet++. A single-channel reference EEG dataset including 23 collections of motion-corrupted & standard authentic EEG data of PhysioNet is used to train and evaluate each of the 11 deep neural network DNN models. In this paper, the leave-one-out cross-validation approach was applied. Three renowned benchmarks are used to gauge the deep learning architectures' performances: viz.

Deepak Pancholi et al. [22]designed a methodof ICA & CCA are used to eliminate the artefacts. Measures of performance including Lambda, Spectrum Displacement (Pdis), Difference Signal to Noise Relationship (DSNR), and RMSE, or root mean square error, have been taken into account while assessing the electroencephalogram (EEG) signal. The execution time of the methods is also evaluated in order to gauge their computational efficiency. In this work, we firstly define the properties of the electroencephalography (EEG) signal, followed by different types of artefacts, and lastly the encoding examination of several methods of elimination. Gholami-Boroujeny et al. [23]have evaluated the effectiveness of a linear ANC method based on lowest means squared adaptation with a novel linear adaptable noise cancelling (ANC) relying on a multi-layered perceptron neural networks to improve the voice ABR. Using spoken ABR data, the approaches' efficacy is evaluated using two distinct SNR indicators: the total SNR and the regional SNR at the response's basic frequency. The findings demonstrate that, in particular, when the SNR of the speech being recorded ABR is low, nonlinear neuronal network-based ANC outperforms the linear ANC and can shorten the necessary record duration. Roy, Vandana et al [24] presented valuation of six distinctive methods—a combination of the following: the independent component analysis (ICA), conventional correlation analysis (CCA), the discrete wavelet change and stationary waves transform—each of the above conjunction approaches is used on the set of scientific mode breakdown, inherent mode functions for EEG motion artefact cancellation. The goal of the present study is to develop an effective BSS based technique for successfully eliminating the EEG motion artefacts.

Advancements in artifacts removal techniques are continuously being developed, with a focus on improving accuracy and efficiency. For instance, the combination of Ensemble Empirical Mode Decomposition (EEMD) with Canonical Correlation Analysis (CCA) and Wavelet Transform (WT) has shown superior results in motion artifacts removal (Stalin et al., 2021). Future research could explore integrating these methods with neural network-based approaches for even more robust artifacts eradication. Interestingly, some contradictions and challenges exist in the field. While some studies advocate for single-channel EEG processing (Ranjan et al., 2022; Stalin et al., 2021), others emphasize the benefits of multi-channel approaches (Radüntz et al., 2017). This discrepancy presents an opportunity for future research to develop adaptive systems that can effectively handle both single and multi-channel EEG data. In conclusion, the future of intelligent EEG signal processing lies in developing more sophisticated, real-time capable, and versatile algorithms. The integration of machine learning techniques, such as the artificial neural network approach achieving 95% accuracy in artifacts classification (Radüntz et al., 2017), with advanced signal processing methods like the hybrid de-noising framework combining modified EMD and optimized Laplacian of Gaussian filter (Ranjan et al., 2022), holds great promise. Additionally, the potential for improved brain-computer interface applications through enhanced artifacts removal techniques, as demonstrated by the adaptive noise cancelling scheme achieving over 95-99.9% correlation between raw and processed signals in non-artifacts regions (Kilicarslan et al., 2016 [28]), further underscores the importance of continued research in this field.

Overall it can be concluded that it is required to design improved NN based approach for completely eliminating effect of high peak eye blinks.

III. MULTIMODE PRE–PROCESSING

The EEG signals are captured from multimode frequency bands. There were many methods designed to de noise EEG signals using multimode decomposition approaches. The Ensemble empirical mode decomposition (EEMD) method is most frequently used for EEG artifacts eradicationK. T.Sweeney et al. 2013). Independent component analysis, or ICA for short, is a widely used technique in EEG to remove artefacts and split sources to many mode signals from EEG origins (Benning, K., et al 2019 [9]). But the ICA approaches are unable to eliminate nonlinear artifacts present in the EEG signals such as eye blinks.Additionally in case of source (electrodes) dependency as in case of EEG motion artifacts ICA is unable to decompose efficiently.

In recent times many hybrid combination of EEMD with other processing methods were proposed to improve performance. Researchers assess the effectiveness of hybrid combinations like EEMD along with conventional fast CCA decomposition and DWT is optional as suggested for Brain computer interface uses by (D. Pancholi, et al 2019).This section sequentially describes various pre-processing methods for EEG artifacts removal.

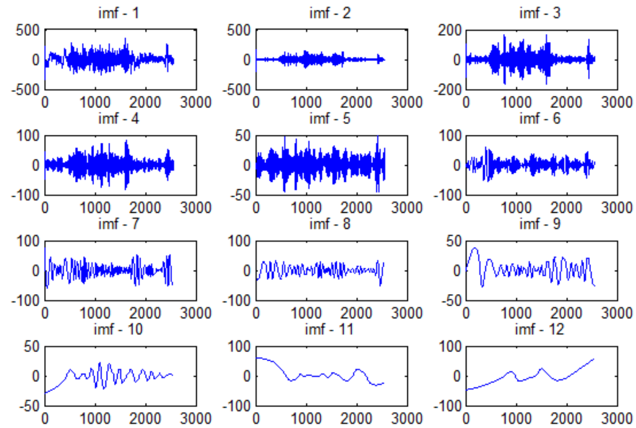
EEMD:

Complicated, nonlinear, and irregular signals such as EEG are broken down to smaller components referred to as Intrinsic Mode Functions (IMFs) using an advanced signal processing technique called EEMD. To address some of its shortcomings, such as mode mixture, the EMD, is expanded into EEMD.The EEMD uses an iterative process called sifting to break down a signal into many intrinsic mode functions (IMFs). The first-level EEG signal's X(t)'s lower and upper envelope means are combined to form the IMF1 Deepak et al [22]. The residual signal is obtained by subtracting IMF1 from X(t). The remained signal amount of energy is nearly zero at the end of each iterations of this process, which is the stopping condition.

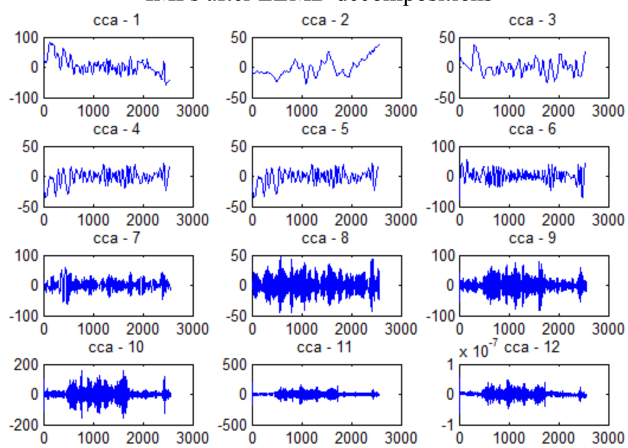
CCA

According to Roy et al. [24], the standard current CCA algorithm assumes that X[n] along with Y[n] be two sets of random variables. Let X[n] represents the input vector of the (t) matrix. The temporal correlations of Y[n] can be characterised as follows: 2D convolutions with X[n] vectors using the linear convolution masked as [1 0 1], his is calculated in covariance matrix C in xx and yy and xy directions. The extracted IMFs using EEMD and CCA components are illustrated in the Figure 3. It is clear that EEMD start from higher to lowered frequency. And CCA decompose from lower to higher frequency components.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, April 2025
Impact Factor: 7.67



IMFs after EEMD decompositions



CCAs after CCA decompositions

Figure 3 Multi-Mode decomposition of EEG signal.

IV. EEMD-CCA-DWT

Usually in order to filter the artifacts and to improve the SNR performance the EEMD CCA is combined further to DWT decompositions. That main advantage is to improve SNR performance. The person correlation filter is used for artifacts eradication.

Proposed NN Filter Methodology

The EEG data is first applied to the adaptive NN filter using back propagation NN. And the filtered signal is further applied to the EEMD-CCA de compositions with correlation filter for artifacts eradication. The Figure 4 illustrates the proposed block diagram of the NN based intelligent adaptive EEG artifacts eradication approach. The Figure is illustrated a two-branched (row) process for removing artifacts from EEG data and is a combination of the adaptive NN Filter and conventional EEM-CCA filtering approach.

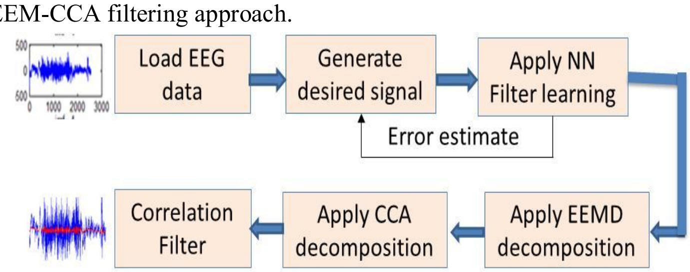


Figure 4 Block diagram of the proposed artifacts eradication approach

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, April 2025
Impact Factor: 7.67

4.1 Proposed NN Approach

In this section the proposed hybrid intelligent NN-EEMD-CCA approach is sequentially described.

Load EEG data: The process begins by loading the raw electroencephalogram (EEG) data.The i[th] EEG signal $EEG(t)_i$ with motion artifacts A_i is represented as

$$EEG(t)_i = EEG_{true} + A_i \quad (1)$$

Generate desired signal: A desired signal d is generated representing the clean EEG is selected from the EEG dataset which is close approximation of true EEG signal without artifacts.The adaptive filter requires the basic desired signal generation as given in Eq.

$$. \quad .d(n) = x(n) - en) \quad (2)$$

This might involve initial filtering or other pre-processing techniques to create an estimate of the artifacts-free signal.

Apply NN Filter learning: A NN is used to learn how to filter the EEG data. The NN is trained to minimize the difference (error) between the generated desired signal and the filtered EEG. The error estimate is fed back to refine the NN filter's performance. This block refines the neural network's filtering capabilities based on the error estimate. This iterative process is likely designed to achieve optimal artifacts reduction. The weight iodation based flow chart of the proposed NN filter adoption is represented in the Figure 5.

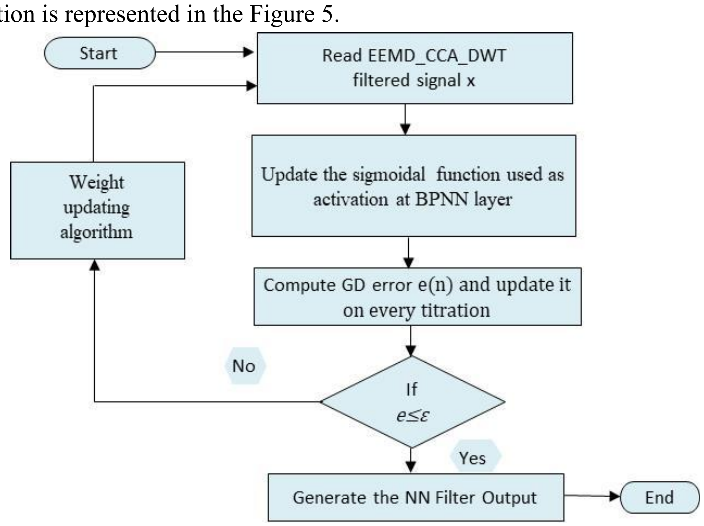


Figure 5the flow chart of the suggested NN Filter design approach

The process of weight adoptionbegins by reading a filtered signal 'x' which is the output of a pre-processing step involving EEMD, and CCA, and optimally DWT night be used. The gradient decent based NN filter weight adoption is proposed. he sigmoid function is used as the activation function in the Back-propagation Neural Network (BPNN) layer.

$$\sigma(z) = 1 / (1 + e^{(-z)}) \quad (3)$$

The Gradient Descent (GD) error e(n), is computed at each iteration as defined by the (2). The algorithm checks if the error (e) is less than or equal to a predefined threshold (ε). This threshold determines the convergence criteria. The weight updating algorithm of the adaptive NN filter is represented in Algorithm 1.

Algorithm 1 NN Filter Weight Adaption
Initialization: Read signal x. Initialize weights (wi) and biases (bi) randomly or using a specific initialization strategy select desired output d. **Forward Pass:** Calculate the output of each neuron: as Weighted sum of inputs + bias $zi = wiTx + bi$ (4) Activation function: is a Sigmoid function here $yi = \sigma(zi)$ (5) Combine neuron outputs

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, April 2025
Impact Factor: 7.67

ŷ = f(y1, y2,...,ym) (6) Update weights of NN filter: calculating gradients of the loss function e(n) = L(ŷ, d) with respect to weights and biases $wi(n+1) = wi(n) - \eta * \nabla wiL(\hat{y}, d)$ (7) $bi(n+1) = bi(n) - \eta * \nabla biL(\hat{y}, d)$ (8) Where η is the learning rate. The gradient calculations (∇) involve chain rule application through the network layers. Error Check: if e(n) ≤ ε, then stop; else go to step 2. Update the weight and iterate for optimal solustiosn
end Algorithm

Apply EEMD decomposition: Empirical Mode Decomposition (EEMD) is further applied to the signal. EEMD is a signal processing technique that decomposes complex signals into a series of intrinsic mode functions (IMFs). It helps separate different frequency components of the signal which may help isolate the artifacts from the EEG signal.By adding and assessing Gaussian noise, the EEMD has been utilized to decompose the signal into several intrinsic mode functions (IMF). The residual signal and all of the IMFs are combined to create the output, which is;

y= $IMFs = \sum_{j=1}^{l} f_j + p_l$ (9)

EEMD output IMFs are generated using the IMF and residual $R_n(t)$ accumulation eq as;

$$\boldsymbol{x(t)} = \sum_{i=1}^{N} IMF_i((t) + R_n(t) \quad (10)$$

Apply CCA decomposition: Canonical Correlation Analysis (CCA) decomposition is performed on the filtered signal. CCA is a statistical method to identify correlated components within data. This may help isolate the artifacts from the underlying brain activity.The linear correlation among the two sets of statistical variables is ascertained by the CCA approach using the data's covariance and variability matrices. A and B, a pair of pairs, is intended to be:

$$\mathrm{B}_v = [\mathrm{b}_{11}, \dots \mathrm{b}_{12}, \dots . . \mathrm{b}_{1\mathrm{N}}]^{\mathrm{T}} \quad (11)$$

$\mathrm{A}_u = [\mathrm{a}_{11}, \dots \mathrm{a}_{12}, \dots . . \mathrm{a}_{1\mathrm{M}}]^{\mathrm{T}}$ (11)

Correlation Filter: A correlation filter is applied to the EEG data. This type of filter is often used to enhance specific signal components or suppress noise. In this context, it likely pre-conditions the signal before the further decomposition steps. A sample filtered signal is displayed above this block.

Overall theproposed NN-EED-CCA is a NN and decomposition basedapproachaim to remove artifacts from the EEG signal. The output from NN filter would likely be compared and combined with EEMD-CCA filter stage. The filtered output might be adaptively selected based on a specific performance metric. The ultimate goal is to produce a clean EEG signal free from unwanted noise and interference.

V. RESULTS AND DISCUSSIONS

In this section various results and quantitative evaluation of the proposed NN based adaptive EEG artifacts removal method are presented. Figure 6 presented the input EEG signals used for evaluation in this paper. It can be clearly observed that the artifacts with eye blinks might have significant magnitude in the rage from 1000 to 2000mv. The EEG data are available on the github library database in the .mat form. The overall data contains 16 EEG data with EMG and EOG artifacts.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, April 2025
Impact Factor: 7.67

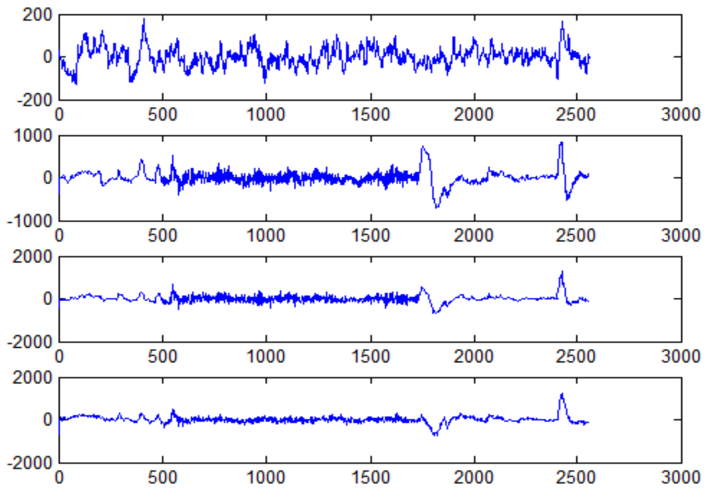


Figure 6 input signals used for evaluation in paper. First row is true EEG and 2,3 and 4th rows are artifacts signals.

The input artifacts signal and the comparison of FIR filtered noisy signal n(t) are represented in the Figure 7. In order to do this the random FIR filter is applied on the EEG signal under noise environment. The additive noise x(t) is generated and signal is filtered using the IR filter to produce the desired EEG signals.

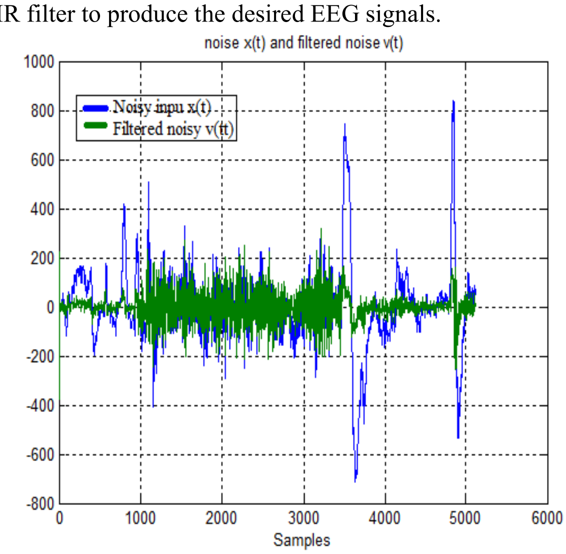


Figure 7results of noisy filtered desired EEG signal d generation for NN filter design

The results of the references EEG signal and the noisy filtered desired input signal are shown in the Figure 8 after the NN filtering. It can be clearly observed that the higher peaks EEG signals are reduced to range of the 100 to 200 mv EEG signal range. Thus the use of the adaptive NN filter is capable of learning and optimizing the sigmoidal or signum functions as member function. The desired noisy signal is pretty close approximations of true EEG signal. Thus Figure 8 illustrates the efficiency of proposed NN filter.

DOI: 10.48175/568

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, April 2025
Impact Factor: 7.67

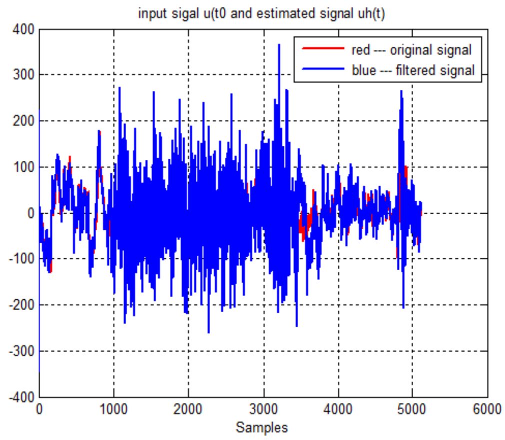


Figure 8 A referenceddesired noisy signal and filtered NN signal results

The result so filtered true Artifact EEG removal using the hybrid proposed combinati0on of NN-EEMD-CCCA filter with correlation filtering are illustrated in the Figure 9. The filtered signal is pretty close approximation of true EEG signals or reference EEG signal. The final outcome of the decomposed recovers IMFS after filtering are shown in the Figure 10. It can be clear from the Figure as the decomposition level increases the final signal is getting close to true EEEG signal.

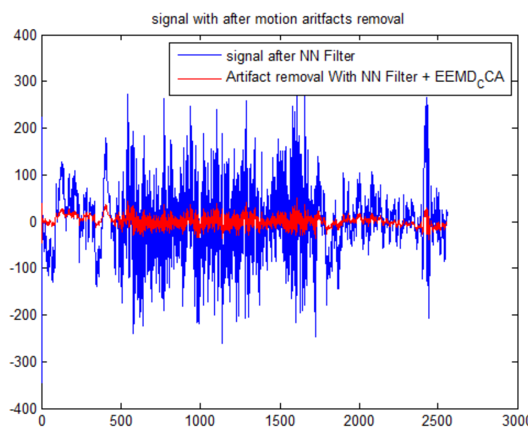


Figure 9 the NN-EEMD-CCA results after filtering.

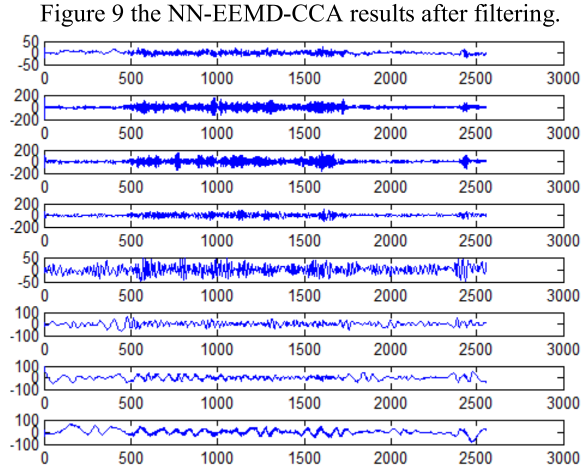


Figure10recovered filtered IMFs after NN-EEMD-CCA

DOI: 10.48175/568

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, April 2025
Impact Factor: 7.67

TheFigure 10presents a series of recovered filtered IMFs after proposed NN-EEMD-CCA. The distinct IMF are obtained through a noise-assisted empirical mode decomposition (NN-EEMD) followed by CCA decomposition. The figure suggests a successful decomposition into constituent parts, which might then be used for analysis or feature extraction in fields like signal processing, biomedical engineering, or geophysics. Also it can be observed from final IMF that the proposed NN based filter preserved the true nature of EEG signal much better and minimize the ocular eye blinks peaks.

5.1 Parametric Evaluation

The parametric quantitative results of proposed method adaptive NN based filtering approach are evaluated in this section. The results quality is justified by comparing the paramedicperformance with equivalent state of art methods.

State of art comparisons

In this section the parametric studies are carried out for the state of art compactions. The statistical parameters used for evaluations are as follows.

DSNR=$10log_{10}(\left(\frac{\sigma_s{}^2}{\sigma_{after}{}^2}\right)$-10 $log_{10}(\left(\frac{\sigma_s{}^2}{\sigma_{before}{}^2}\right)$ (12)

The Figure 11 illustrated the ROC curve for the proposed NN-EEDM-CCA approach the higher specificity and higher Area and larger slope of ROC curve illustrated the accuracy of proposed method.

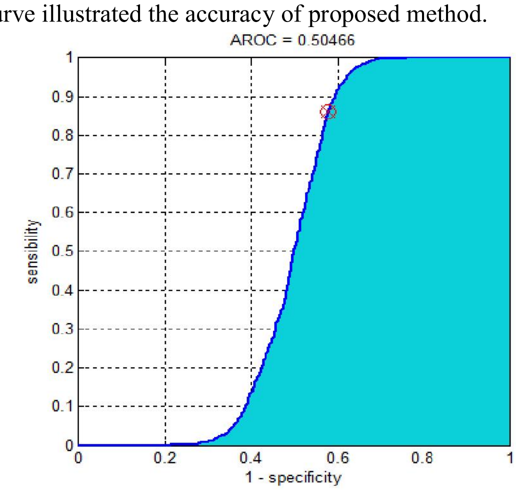


Figure 11 the ROC curve of the proposed Filter approach

The parametric performance of state of art method of the Deepak et a [22] and the Roy Vandan et al [20] are illustrated in the Table 1 and Table 2. The Table 1 shows a comparison of ROC performance between the method of Deepak Pancholi et al. [22] and a proposed neural network (NN). The proposed NN significantly outperforms Deepak Pancholi's method. The proposed NN achieved a sensitivity of 0.85977, a considerable increase from Deepak Pancholi's 0.401. This represents a more than double improvement in the model's ability to correctly identify positive cases.While the proposed NN shows a slightly higher AROC of 0.50466 compared to 0.49073 for Deepak Pancholi's method. A higher AROC generally indicates better overall performance.The proposed NN boasts 64.1602% accuracy, exceeding Deepak Pancholi's method's 61.04% accuracy

Table 1 Comparison of ROC performance

Methods	Sensitivity	AROC	Accuracy
Deepak Pancholi et al [22]	0.401	0.49073	61.04 %
Proposed NN	0.85977	0.50466	64.1602%

Similarly the quantitative comparisons of the parametric performance of different filtering approaches are presented in the Table 2. Proposed NN method demonstrates superior performance across all three parameters compared to the other methods (EEMD-CCA, EEMD-ICA-DWT, and EEMD-CCA-DWT as refer by Roy, Vandana et al) at a 10dB SNR

Table 2 Parametric performance comparison is presentedwith Roy, Vandana et al [24] AT 10 dB SNR

Parameter	**EEMD CCA [24]**	**EEMD ICA DWT [24]**	**EEMD CCA DWT [24]**	**Proposed NN EEMD-CCA**
DSNR	8.611	19.199	25.9530	**31.8590**
PSD improvement	0.9983	2.6831	0.2368	**2.7325**
Lambda	33.009	85.724	79.2630	**85.7937**

The Proposed NN achieves the highest DSNR (31.8590) as in Table 2, significantly outperforming with 6 dB mark over. EEMD-CCA-DWT (Roy, Vandana et al) as the second-best result of 25.9530 dB.While EEMD_ICA_DWT shows a relatively high PSD improvement (2.6831), the Proposed NN achieves a slightly better result (2.7325). EEMD_CCA_DWT shows the worst performance in this parameter.

Lambda: Both the Proposed NN and EEMD_ICA_DWT achieve similar high Lambda values (85.7937 and 85.724 respectively). EEMD_CCA_DWT exhibits a lower Lambda value.

It can be clearly observed form the tables 1 and 2 that the proposed method offers significant improvement in DSNR and PSD performance over existing approaches. The Proposed NN method consistently outperforms the other methods in terms of DSNR and offers comparable or better performance concerning PSD improvement and Lambda. This suggests the Proposed NN is a more effective approach for the task under consideration at the specified SNR.

Higher DSNR values indicatelower RMSE and thus improved signal quality and suggest better accuracy in artefact removal. The results demonstrate that the proposed NN-based approach effectively enhances EEG signal clarity by minimizing motion artefacts.The PSD improvement of nearly 0.15 is offers over ICA approach and for CCA it is 2.4 times more.

Discussion and Practical Implications

The proposed neural network-based adaptive filtering approach for intelligent EEG signal processing and artifacts removal has significant practical implications across various domains. The adaptive nature of the neural network approach suggests potential for developing personalized artifacts removal techniques tailored to individual EEG characteristics. This personalization could further improve the accuracy and effectiveness of EEG analysis across diverse populations. Additionally, this work demonstrates the successful application of machine learning techniques to a critical biomedical signal processing challenge, contributing to the on-going integration of artificial intelligence in healthcare.While the proposed neural network-based adaptive filtering approach shows promise for intelligent EEG signal processing and artifacts removal, several limitations should be acknowledged. Firstly, the method's performance may vary depending on the complexity and diversity of artifacts present in real-world EEG recordings, potentially limiting its effectiveness in certain scenarios. Secondly, the approach's reliance on training data raises concerns about its generalizability across different EEG acquisition systems and patient populations.

The practical implications of this work on intelligent EEG signal processing and artifacts removal include:

Improved accuracy of EEG analysis: By effectively removing motion artifacts like eye blinks and muscle movements, the proposed neural network-based adaptive filtering approach can significantly enhance the quality and reliability of EEG signals. This allows for more accurate analysis and interpretation of brain activity patterns.

Enhanced diagnostic capabilities: Cleaner EEG signals enable better detection and characterization of neurological conditions and brain disorders. This can lead to improved diagnostic capabilities and more precise monitoring of brain function in clinical settings.

Advancement of brain-computer interfaces: The artifacts removal techniques developed here can be applied to improve the performance of brain-computer interface systems by providing cleaner EEG inputs. This has potential applications in assistive technologies and human-machine interaction.

More efficient EEG processing: The proposed neural network approach offers computational efficiency compared to some existing methods. This allows for faster processing of EEG data, which is beneficial for real-time applications.

Broader applicability of EEG: By addressing common artifacts issues, this work makes EEG analysis more robust and applicable in a wider range of settings, including ambulatory and naturalistic environments where motion artifacts are prevalent.

Improved research capabilities: For neuroscience and cognitive science researchers, having access to cleaner EEG signals enables more nuanced studies of brain function and cognition.

Potential for personalized filtering: The adaptive nature of the neural network approach suggests potential for developing personalized artifacts removal techniques tailored to individual EEG characteristics.

VII. CONCLUSIONS AND FUTURE WORKS:

This research proposed an adaptive neural network (NN) based filter to remove motion artifacts, specifically eye blink (EOG) and muscular (EMG) artifacts, from EEG signals. The NN filter uses back propagation to learn the features and nature of the EEG signals. The filtered signal is further processed using ensemble empirical mode decomposition (EEMD) and canonical correlation analysis (CCA) decompositions along with correlation filtering for artifacts removal. Paper has considered motion artefacts database based on EOG and EMG motion artifacts. The most of previous filter are unable to eliminate the eye blink impact completely and are sensitive to reduction in amplitudes. The gradient decent problem is the effectiveness of the adaptive neural network (NN) filter employing back propagation based NN.

It is concluded that the proposed NN based filter is capable of accurately learn the data and is capable of eliminating the impact of EOG amplitude peaks. The paper also suggested parametric evaluation of different EEG data in order to perform the necessary artefact reduction techniques.

The proposed method is compared with existing approaches and shows significant improvement in peak signal-to-noise ratio (PSNR) and power spectral density (PSD) performance. The paper concludes that the NN-based filter is capable of accurately learning the data and effectively eliminating the impact of EOG amplitude peaks.The Proposed NN outperforms EEMD-CCA-DWT in DSNR and PSD, with a 6 dB mark over EEMD_CCA_DWT. Both NN and EEMD_ICA_DWT achieve high Lambda values, with EEMD_CCA_DWT showing the worst performance.The PSD improvement is nearly 0.15 over the ICA approach and 2.4 times more than CCA.

The ROC curve for the proposed NN-EEMD-CCA approach shows higher specificity, area, and slope. The proposed neural network significantly outperforms Deepak Pancholi's method, achieving a sensitivity of 0.85977 and a slightly higher AROC of 0.50466, resulting in 64.1602% accuracy, surpassing Deepak Pancholi's 61.04% accuracy.

Quantitative parametric evaluation demonstrates the superiority of the proposed method compared to state-of-the-art techniques.

7.1 Future Research Scopes

The computational requirements for real-time implementation in resource-constrained environments may pose challenges for widespread adoption in future. Furthermore, the method's ability to distinguish between genuine brain activity and artifacts-like neural signals requires further investigation in future to ensure preservation of clinically relevant information. Lastly, the lack of standardized evaluation metrics for artifacts removal techniques makes direct comparisons with existing methods challenging, necessitating further validation studies to establish the approach's superiority in various clinical and research contexts.

Although proposed NN filter is accurate and preserves the signal well but an extension of scope future research should focus on addressing the limitations of the proposed neural network-based adaptive filtering approach. This may include expanding the training dataset to encompass a wider range of artifacts types and EEG recording conditions, thereby improving the method's robustness and generalizability. Investigating the integration of unsupervised learning techniques could enhance the algorithm's adaptability to novel artifacts patterns. Additionally, optimizing the computational efficiency of the approach through hardware acceleration or algorithm refinement would facilitate its implementation in real-time clinical settings. Further studies should explore the method's performance in distinguishing between artifacts and clinically significant EEG abnormalities, potentially incorporating domain expertise to fine-tune the filtering process. Collaborative efforts to establish standardized evaluation metrics for artifacts removal techniques would enable more meaningful comparisons between different approaches. Finally, conducting large-scale clinical trials across diverse patient populations and EEG acquisition systems would provide valuable insights into the method's practical utility and potential impact on EEG-based diagnoses and research outcomes.

REFERENCES

[1]. Selvan, S., & Srinivasan, R. (1999). Removal of ocular artifacts from EEG using an efficient neural network based adaptive filtering technique. IEEE Signal Processing Letters, 6(12), 330–332. https://doi.org/10.1109/97.803438

[2]. Erfanian, A., & Mahmoudi, B. (2005). Real-time ocular artifact suppression using recurrent neural network for electro-encephalogram based brain-computer interface. Medical & Biological Engineering & Computing, 43(2), 296–305. https://doi.org/10.1007/bf02345969

[3]. Yang, B.-H., Wang, Q., He, L.-F., & Lin, L. (2015). Fast removal of ocular artifacts from electroencephalogram signals using spatial constraint independent component analysis based recursive least squares in brain-computer interface. Frontiers of Information Technology & Electronic Engineering, 16(6), 486–496. https://doi.org/10.1631/fitee.1400299

[4]. Ye, Y., Zhang, Z., Cheng, Y., He, W., & Hou, M. (2016). Combining Nonlinear Adaptive Filtering and Signal Decomposition for Motion Artifact Removal in Wearable Photoplethysmography. IEEE Sensors Journal, 16(19), 7133–7141. https://doi.org/10.1109/jsen.2016.2597265

[5]. P. Sharma, "Removal of Artifacts In EEG Signals Using Sign Based LMS Adaptive Filtering Techniques," 2023 1st International Conference on Innovations in High Speed Communication and Signal Processing (IHCSP), BHOPAL, India, 2023, pp. 199-203, doi: 10.1109/IHCSP56702.2023.10127136..

[6]. Behera, Sandhyalati & Mohanty, Mihir & Mohapatra, Saumendra. (2023). Design of optimized adaptive filter for artifact removal from EEG signal. Journal of Statistics & Management Systems. 26. 201-212. 10.47974/JSMS-959.

[7]. Chen, X., Chen, Q., Zhang, Y., & Wang, Z. J. (2018). A novel EEMD-CCA approach to removing muscle artifacts for pervasive EEG. *IEEE Sensors Journal*, *19*(19), 8420-8431.

[8]. K. T.Sweeney, S. F. McLoone and T. E. Ward,"The use of Ensemble Empirical Mode Decomposition with Canonical Correlation Analysis as a Novel Artifact Removal Technique", IEEE Transactions Biomedical Engineering,2013,60(1), pp. 97-105.

[9]. Benning, K., Menzel, M., Reuter, J.A., Axer, M. (2021). Independent Component Analysis for Noise and Artifact Removal in Three-Dimensional Polarized Light Imaging. In: Amunts, K., Grandinetti, L., Lippert, T., Petkov, N. (eds) Brain-Inspired Computing. BrainComp 2019. Lecture Notes in Computer Science(), vol 12339. Springer, Cham. https://doi.org/10.1007/978-3-030-82427-3_7

[10]. D. Pancholi, M. Vekatadri and P. Rawat, "EEG Motion Artifacts Removal for Robotic Motion Control Using Brain Computer Interface," 2019 4th International Conference on Robotics and Automation Engineering (ICRAE), Singapore, 2019, pp. 207-212, doi: 10.1109/ICRAE48301.2019.9043777.

[11]. J. Gao, C. Zheng, and P. Wang, "Online removal of muscles artefact from electroencephalogram Signal Based on Canonical Correlation Analysis", Clinical EEG and Neuroscience, 2010, 40(1), pp. 53-59.

[12]. Roy Vandana, Shukla Shailja, Piyush Kumar Shukla, Rawat Paresh.. "Gaussian Elimination-Based Novel Canonical Correlation Analysis Method for EEG Motion Artifact Removal". Journal of Healthcare Engineering, 2017, 10.1155/2017/9674712 https://doi.org/10.1155/2017/9674712

[13]. Zhang, C., Sabor, N., Luo, J. *et al.* Automatic Removal of Multiple Artifacts for Single-Channel Electroencephalography. *J. Shanghai Jiaotong Univ. (Sci.)* **27**, 437–451 (2022). https://doi.org/10.1007/s12204-021-2374-5

[14]. Hemant Amhia and A. K. Wadhwani, Designing an Optimum andReduced Order Filter for Efficient ECG QRS Peak Detection and Classification of Arrhythmia Data, Hindawi Journal of Healthcare Engineering Volume 2021, Article ID 6542290, 17 pages https://doi.org/10.1155/2021/6542290

[15]. VYAS, P. K., RAWAT, P., & KHATRI, S. (2011). Back propagation based adaptive noise chancellor. *International Journal of Computer Technology and Electronics Engineering (IJCTEE)*, *1*, 14-16.

[16]. Prerna Kumari[1], Deepak Singh[2] "Filter Design and Amplitude Shaping Methodologies for De-Noising Digital Hearing Aids", International Journal of Engineering and Innovative Technology (IJEIT) Volume 10, Issue 11, May 2021

[17]. Maddirala, A.K., Veluvolu, K.C. Eye-blink artifact removal from single channel EEG with *k*-means and SSA. *Sci Rep* **11**, 11043 (2021). https://doi.org/10.1038/s41598-021-90437-7

[18]. L. Wang, S. Zhang and F. Lu, "Pulsar Signal Denoising Method Based on Empirical Mode Decomposition and Independent Component Analysis," 2018 IEEE Chinese Automation Congress (CAC), Xi'an, China, 2018, pp. 3218-3221, doi: 10.1109/CAC.2018.8623656.

[19]. X. Chen, Q. Chen, Y. Zhang and Z. J. Wang, "A Novel EEMD-CCA Approach to Removing Muscle Artifacts for Pervasive EEG," in IEEE Sensors Journal, vol. 19, no. 19, pp. 8420-8431, 1 Oct.1, 2019, doi: 10.1109/JSEN.2018.2872623.

[20]. S. Shukla, V. Roy and A. Prakash, "Wavelet Based Empirical Approach to Mitigate the Effect of Motion Artifacts from EEG Signal," 2020 IEEE 9th International Conference on Communication Systems and Network Technologies (CSNT), Gwalior, India, 2020, pp. 323-326, doi: 10.1109/CSNT48778.2020.9115761.

[21]. Mahmud, S., Hossain, M.S., Chowdhury, M.E.H. et al. MLMRS-Net: Electroencephalography (EEG) motion artifacts removal using a multi-layer multi-resolution spatially pooled 1D signal reconstruction network. Neural Comput & Applic 35, 8371–8388 (2023). https://doi.org/10.1007/s00521-022-08111-6

[22]. Deepak Pancholi Dr. Rajeev Goyal. and Dr. Paresh Rawat, "EEG Artifact Removal Using Supervised Learning based Neural Filter", Eur. Chem. Bull. 2023,12(issue 8), 8636 – 8648

[23]. Gholami-Boroujeny, S., Fallatah, A., Heffernan, B.P. *et al.* Neural network-based adaptive noise cancellation for enhancement of speech auditory brainstem responses. *SIViP* **10**, 389–395 (2016). https://doi.org/10.1007/s11760-015-0752-x

[24]. Roy, Vandana; Shukla, Shailja (2019). Designing Efficient Blind Source Separation Methods for EEG Motion Artifact Removal Based on Statistical Evaluation. Wireless Personal Communications, (), –. doi:10.1007/s11277-019-06470-3

[25]. Stalin, S., Roy, V., Jain, A., Shukla, P. K., Zaguia, A., Shukla, P. K., & Khan, M. M. (2021). A Machine Learning-Based Big EEG Data Artifact Detection and Wavelet-Based Removal: An Empirical Approach. Mathematical Problems in Engineering, 2021, 1–11. https://doi.org/10.1155/2021/2942808

[26]. Radüntz, T., Hochmuth, O., Meffert, B., & Scouten, J. (2017). Automated EEG artifact elimination by applying machine learning algorithms to ICA-based features, Journal of Neural Engineering, 14(4), 046004. https://doi.org/10.1088/1741-2552/aa69d1

[27]. Ranjan, R., Sahana, B. C., & Bhandari, A. K. (2022). Motion Artifacts Suppression From EEG Signals Using an Adaptive Signal Denoising Method. IEEE Transactions on Instrumentation and Measurement, 71, 1–10. https://doi.org/10.1109/tim.2022.3142037

[28]. Kilicarslan, A., Grossman, R. G., & Contreras-Vidal, J. L. (2016). A robust adaptive denoising framework for real-time artifact removal in scalp EEG measurements, Journal of Neural Engineering, 13(2), 026013. https://doi.org/10.1088/1741-2560/13/2/026013

DECLARATION

This manuscript is an original part of our research and has not been published elsewhere. The data used is available worldwide and is referenced within the text.

All authors have consented to the submission of this work, and there are no conflicts of interest associated with it.

It is to declare that no external funding was obtained for this manuscript.

The manuscript has not been copied from any other source or work. It utilizes the comprehensive global database of facial images, with pertinent links included in the references.

Author 1 was responsible for validating all results and preparing the manuscript. Author 2 revised the presentation, proofread the script, made grammatical corrections, and provided justifications for comments.

ACKNOWLEDGEMENT

The authors express their gratitude to everyone directly or indirectly involved in the research. They also appreciate all the researchers cited in the manuscript for their indirect contributions to the work.