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Enhanced Epileptic Seizure Classification with Ocular Artifact Removal and Modified Gated Recurrent Unit

Vinod Prakash [1], Dharmender Kumar [2], Deepak Kumar [3]
[1] FGM Government College, Adampur, Hisar Haryana, India
[2,3]Guru Jambheshwar University of Science and Technology, Haryana, India
[1)]vbhadrecha@gmail.com, [2)]dharmender@gjust.org, [3)]drdeepakjanghu@gmail.com
*Corresponding author

Abstract

Background: Electroencephalography (EEG) is non-invasive technique has the capability to detect minuscule variations in voltage that arise from the movement of ionic currents within the neurons present in the cerebral cortex. These recordings can help to diagnose brain disorders such as tumours, seizures specially epileptic seizures. But these EEG recordings are often distorted by undesired noise due to eye movements and blinking, known as ocular artifacts.
Objective: Detection and removal of artifact present in EEG recordings is crucial one. These artifacts are of same signal frequencies and overlapped with pure EEG signals. During the analysis of these signals, the classification results may varies due to non-availability of artifact free signals. The proposed study is two-step process that initialize with detection and removal of ocular artifact arise due to eye blink and eye movement in UCI epileptic dataset. The deep learning based modified Gated Recurrent Unit is applied for epileptic seizure classification.
Methods: The study focused on removing ocular artifacts with Independent Component Analysis - Discrete Wavelet Transforms, employing an optimized wavelet function. After successfully removing the ocular artifact, the next step involved classifying epileptic seizures using a deep learning model modified Gated Recurrent Unit (GRU)**.**
Results: The results of this study are compared to outcomes obtained from analysing the contaminated UCI epileptic EEG dataset. The findings showed that clean data produced superior results in terms of accuracy, precision, recall, and F1-score. Remarkably, the analysis demonstrates significant improvement in classification accuracy of 99.50%.
Conclusion: The Modified-GRU model enhances electroencephalography-based epileptic seizure classification outcomes, demonstrating its potential for developing accurate and reliable real-world EEG-based Brain Computer Interface (BCI) and ensures the potential for continued impact in the field of medical signal processing.

Keywords: Epilepsy classification, Ocular artifact, Discrete Wavelet Transform, Long Short Term Memory, Gated Recurrent Unit.

1. Introduction

Electroencephalography (EEG) is a technique used for recording the brain's natural electrical impulses and activity over time. This non-invasive approach provides several benefits, like being affordable, readily available, and precisely timing brain activity. [1] The International 10:20 system a widely accepted method for recording of EEG and for this electrodes are placed on the subjects' scalp. Figure 1 depicted visual representation of this system. EEG has the capability to detect minuscule variations in voltage that arise from the movement of ionic currents within the neurons present in the cerebral cortex. Berger [2] pioneered the utilization of EEG signals for capturing brain activity. EEG represents the rhythmic patterns of brain activity at different

frequencies that provides valuable information about normal and abnormal brain function that can help diagnose conditions affecting the brain and nervous system like seizures, tumors and brain injuries. Specific frequency ranges related to human behavioral states referred to by these signals. In EEG signal processing, identifying and removing artifacts is a crucial fundamental step [3], [4], [5]. Researchers have developed various effective methods for eliminating these artifacts, with the goal of overcoming the challenge of artifact removal. Figure 2 depicts ocular artifact, characterized by high-amplitude voltage peaks, is observable in the frontal electrodes such as F7, Fpz, and F8. Adaptive filtering and Kalman filtering are commonly used for filtering EEG signals. The signals can be thought of as "*waves*," and wavelets represent a specific type of wave. The wavelets can effectively eliminate noise and helps to improve the clarity of neural information [6]. Independent component analysis is considered as a effective technique utilized for removing artifacts.
This is accomplished by successfully isolating the EEG signal, which is composed of statistically independent components originating from various sources. The isolated signals from different channels are commonly known as independent components (ICs). However, it is worth noting that in the conventional approach, directly eliminating ICs that contain artifacts can result leads to loss of information embedded in these signals [7].

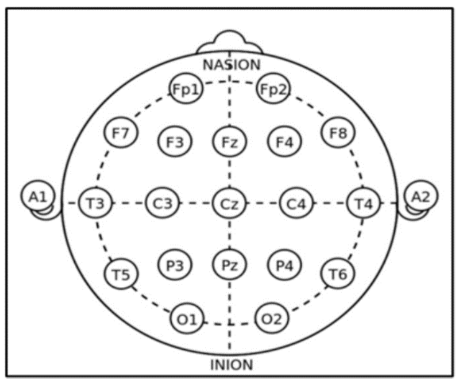

Figure 1. An illustration of 10:20 electrode (channel) placement

Detecting epileptic seizures accurately through EEG is crucial for proper diagnosis and treatment of neurological conditions. Visual inspection of EEG data to identify seizures can be slow and leads to error. To address this challenge, researchers have designed various machine learning and deep learning systems that analyse EEG signals across frequency domains, time scales, and additional metrics to automate seizure detection. These computational approaches aim to classify signals as epileptic versus non-epileptic with greater precision and efficiency than human review alone by leveraging large datasets and advanced algorithms. Definitive diagnosis of brain diseases often necessitates EEG examination. Automated detection tools show promise for improving epilepsy diagnosis by streamlining the analysis of these complex electrophysiological recordings [8]. The limitations of automated systems in identifying epilepsy can be overcome by using deep learning techniques [9]. Deep learning models like CNN, RNN, LSTM, GRU and Autoencoders, are extensively employed in the automated identification of epileptic seizures [10]. RNNs are well-suited for modeling sequential data like time series due to their "memory" of previous computations. They can capture temporal dependencies in variable length sequences. [11] reviewed the LSTM, a common architecture of RNN, as a best performance measures. RNNs

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equipped with a gated mechanism as GRU, have proven to be valuable in the field of sequential inputs like speech or EEG [12]. A modified-GRU approach is introduced herein with the classification results of EEG data contaminated by ocular (EOG) artifacts and the results are also analysed after elimination of EOG artifact utilizing discrete wavelet transform with the optimal wavelet, *db7*.

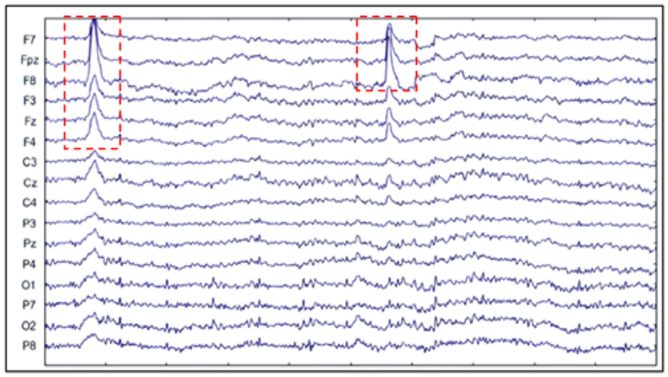

Figure 2. Eye blink artifact in frontal electrodes [6]

The study focuses on classifying epileptic seizures and improving the accuracy of existing deep learning models. Despite their high accuracy in seizure classification, models like CNN, RNN, LSTM, and GRU are affected by artifacts. EEG recordings, which form the basis of these models, often contain both internal and external interferences that distort the EEG signals and lead to inaccurate classification results. Many research articles overlook the issue of eliminating artifacts in epilepsy classification, but this current article offers a solution by achieving better accuracy through the removal of eye blinking and eye movement artifacts. To address the challenge of identifying and removing artifacts prior to classification, the study aims to accomplish the following objectives:

1. Evaluate existing methods for removing eye movement (EOG) artifacts.
2. Assess the efficiency of the ICA-DWT method with optimal wavelet selection.
3. Analyse the performance of epilepsy seizure classification using contaminated EEG recordings and compare it with the results obtained after removing EOG artifacts.

The research paper is structured into several sections. First section presents an introduction to EEG artifacts and the classification of epileptic seizures. The literature review section reviews recent techniques for artifact removal, including filtering methods and deep learning strategies for seizure classification. The background concepts section, explains the terminology used in the methods. The materials and methods section discuss the proposed approach. Lastly, the Results and Conclusion sections discuss the findings and performance analysis, highlighting the significance of the proposed approach.

2. Literature Review

The literature review presents a summary on the use of EEG signals and deep learning techniques in studying brain wave patterns and diagnosing various conditions. Chaudhary and Bhattacharjee

[13] highlight the importance of EEG in identifying and diagnosing conditions such as brain tumors, epilepsy and sleep disorders. Artifacts, unwanted disturbances in EEG signals, can interfere with accurate analysis. Several methods have been proposed to eliminate these artifacts. Inuso et al. proposed the wICA approach, that utilizes wavelets to enhance independent component analysis [6]. Similarly, Akhtar et al. proposed SCICA method, specifically designed to isolate independent components associated solely with artifacts [14]. In this approach, wavelet decomposition method was implemented to eliminate brain activity artifacts.

Exceptional outcomes in addressing EOG artifacts by combined ICA and Haar wavelet were achieved by Morshed [15]. Furthermore, the wavelet decomposition and ICA approach have been explored in subsequent studies to address different artifact types by Yasoda et al. [16] and Grobbelaar et al. [17]. A hybrid method with the integration of DWT and non-local means estimation was presented by Bhobhriya et al. [18] for the EMG artifacts removal.

Deep learning techniques found to be valuable in the early diagnose of epilepsy and prompt medical decision-making. An automated method LAMSTAR was proposed by Nigam and Graupe [19], which achieved a remarkable classification accuracy of 97% in detecting epileptic seizures. The use of wavelet coefficients in EEG signals for classifying EEG information was explored by Güler and Übeyli [20], and a high accuracy rate of 98.68% was obtained using an adaptive neuro-fuzzy inference system.

Recurrent NN based LSTM architectures with softmax classifier was proposed by Golmohammadi et al. [21]. The model obtained satisfactory accuracy of 96.82%. A multilayer perceptron NN-based model for epileptic seizures classification was evaluated by Orhan et al. [22] using DWT and the K-means. In the same vein, Sharmila et al. [23] suggested DWT with the adequate-NN classifier for epilepsy classification. CNN models have shown promise in extracting numerous features, as demonstrated by Radenović et al. [24], but they unable to retain information from previous time stamps, which can impact their performance in analysing EEG signals.

To address this limitation, recurrent neural networks (RNN) use past outputs as inputs and can retain information from previous time stamps, as explained by Choi et al. [25]. TDACNN model to extract spatiotemporal features from time-series data and accurately classify emotions was demonstrated by Bhanusree et al. [26]. Additionally, Chung et al. [27] proposed a modified Gated Recurrent Unit (GRU) model, integrated with an alternative gating mechanism, to address problems of slow convergence, low learning rate, and the vanishing gradient problem in the GRU model.

In summary, the literature review showcases various methodologies that integrate EEG signals with deep learning techniques to analyze brain wave patterns and diagnose conditions such as epilepsy. These studies highlight the effectiveness of methods like wICA, SCICA, wavelet decomposition, LSTM architectures, ANFIS, and modified GRU models, each offering unique contributions to improving the accuracy and efficiency of diagnosing brain-related conditions.

2.1. Filtering Methods for Artifact Removal

The section discuss the filter based ocular artifact removal and deep learning based epileptic classification approaches.

2.1.1. Independent Component Analysis (ICA)

ICA can be seen as an advancement of Principal Component Analysis (PCA). This technique allows for the observed signal to be divided into independent components. Introduced by Herault and Jutten in 1983, ICA has certain limitations. It only enforces independence up to the second order. Moreover, it interprets these components as orthogonal [28]. The clean signals are reconstructed by eleminating the ICs identified as artifacts. Once these components are extracted from the original signals, it becomes possible to reconstruct the clean signals. These ICs are assumed to be non-Gaussian and statistically independent of others signals. ICA is a powerful method for reconstructing original signal sources, provided these signals are statistically independent. The foundations of ICA rest on two key principles [29]:

(i) maximizing non-Gaussianity and
(ii) minimise mutual information

The observed signals are $x_1, x_2, \ldots. x_n$ and source signal consists of the elements $s_1, s_2, \ldots. s_n$, and a mixing matrix called A, with element a_{ij} [30] as described in (1).

$$x(t) = As(t) \tag{1}$$

In the given scenario, matrix A represents an unidentified mixing matrix, while vector *x(t)* represents the observed signals and vector *s(t)* represents the source signals at time, *t*. The nature of this technology appears to be characterized by a lack of prior knowledge concerning both the mixing matrix and the independent signal sources, as depicted in Figure 3.

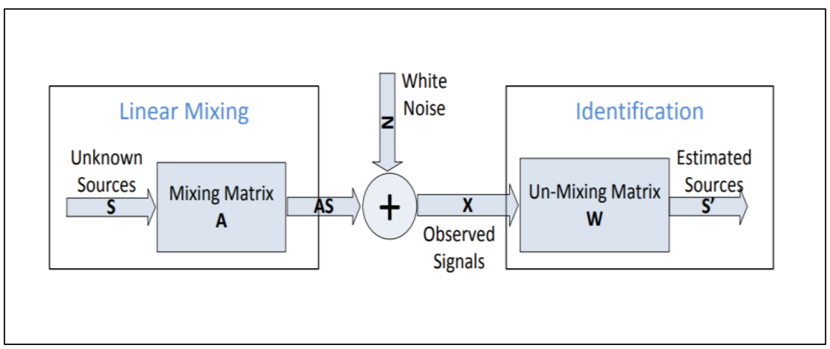

Figure 3. Mixing Matrix in ICA [29]

To estimate the independent components, find the suitable linear combinations of the mixed variables using the inverse matrix *W*, where $W=A^{-1}$ mentioned in (2).

$$\hat{s}(t) = Wx(t) \tag{2}$$

2.1.2. Discrete Wavelet Transform (DWT)

Wavelets are transient waveforms with a mean value of zero that serve as mathematical functions. DWT possesses the capacity to effectively determine the specific location of a function, concurrently in the realms of time and frequency [31]. The wavelet transform is commonly used approach for analysing EEG signals. Through examining the connection between translating and scaling the core wavelet function, WT facilitates the decomposition of a signal in different scales (denoting frequency content) and temporal instances [32]. Donoho and Johnstone [33] introduced the wavelet method for artifact removal. The WT is expressed in (3).

$$f(t) = \sum_{k-1}^{n} A_{j,k}\varphi_{j,k}(t) + \sum_{j=1}^{n}\sum_{k=1}^{n}\Gamma D_{j,k}\Phi_{j,k}(t) \tag{3}$$

where $A_{j,k}$ = approximation and $D_{j,k}$ = detailed coefficients, J=decompose-level; $\varphi(t)$=time-window at time t; n=signal length; Φ= wavelet function and Γ= low and high pass filter. In the DWT, a bandpass filter is utilized for the input signal, which is comprised of a high and low-pass filter designed to operate within defined frequency bands. This filtering separates the input into components based on frequency content. In the process of decomposition, the input signal undergoes division into two coefficients: the Approximation cA[n] and the Detailed cD[n]. [34]. The cD[n] coefficient represents the high-frequency component, while cA[n] represents the low-frequency component [31]. At this initial decomposition stage, these are denoted as *A1* and *D1*. The signals are decomposed at other level, such as *A2, D2, A3, D3* based on particular frequecny. The frequency accuracy of the signal is doubled while the required time is halved at each level. Figure 4 depicted the wavelet transform with decompostion and synthesis process.

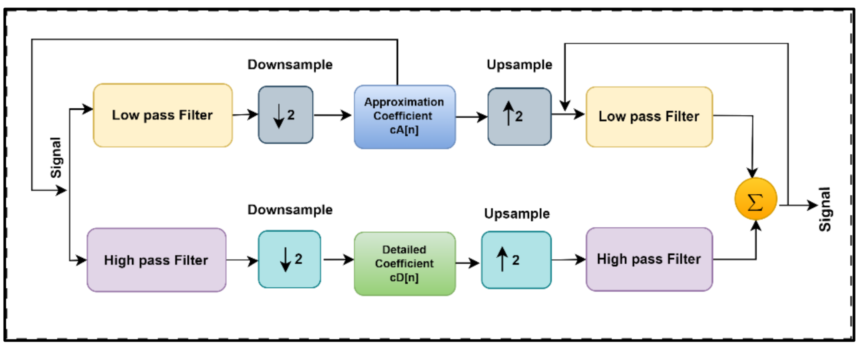

Figure 4. The process of Discrete Wavelet Transform

2.2. Deep Learning Approaches for Seizure Classification

Deep neural networks are constructed upon the foundations of the perceptron model, comprising synthetic neurons. These neurons engage in linear transformations of the input data, with the resultant output being conveyed to the subsequent layer by means of a non-linear activation function [34]. The term "deep" denotes the presence of multiple layers, which provides depth to the neural network architecture. Deep learning technology overcomes the constraints of conventional denoising approaches by automatically detecting and removing artifacts without requiring manual intervention. These are classified as a type of machine learning that implements a layered structure for hierarchical information processing [35].

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2.2.1. Long Short Term Memory (LSTM)

LSTM, introduced by [36], offer an efficient solution for modeling and analyzing sequential data, effectively tackling the challenges of capturing long-range dependencies and handling vanishing gradients in traditional RNN architectures. RNNs often struggle to effectively transmit information from prior time steps to subsequent stages in lengthy sequences, potentially overlooking crucial processed data [37]. The LSTM network is capable of preserving information from the past over an extended period through the use of specialized memory cells. Besides overcoming short-term memory, LSTM gates also regulate data flow. These gates allow the storage of lengthy relevant sequences while ignoring redundant information. The LSTM memory block is composed of three gates: input gate, output gate, and forget gate, as depicted in Figure 5. Here, g and h are the activation function as *sigmoid* and *tanh*. The forget gate enables deciding whether to retain or discard information deemed superfluous.

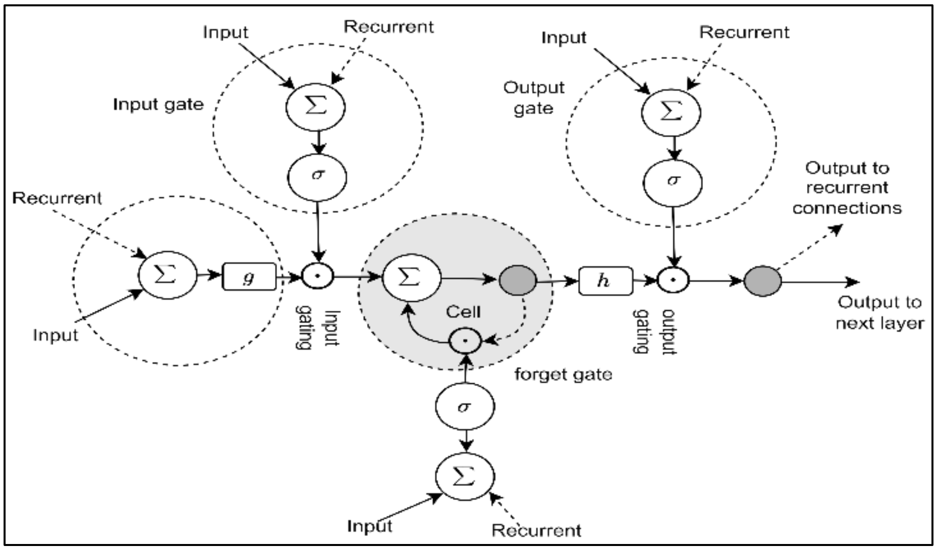

Figure 5. The Representation of LSTM Unit

2.2.2. Gated Recurrent Unit

The Gated Recurrent Unit (GRU) is a type of recurrent neural network. It shares similarities with the LSTM, yet it is a streamlined variation which omits the presence of a distinct memory cell. GRU addresses the issue of vanishing gradients by implementing a standardized LSTM approach [27]. The GRU architecture incorporates update and reset gates. The initial reset gate determines how much hidden state information from prior time steps to preserve for the next, while the update gate decides data for output [37]. Various variations of the GRU model's gates are investigated, demonstrating changes in gate mechanisms [27]. Figure 6 depicts the architecture of the GRU.

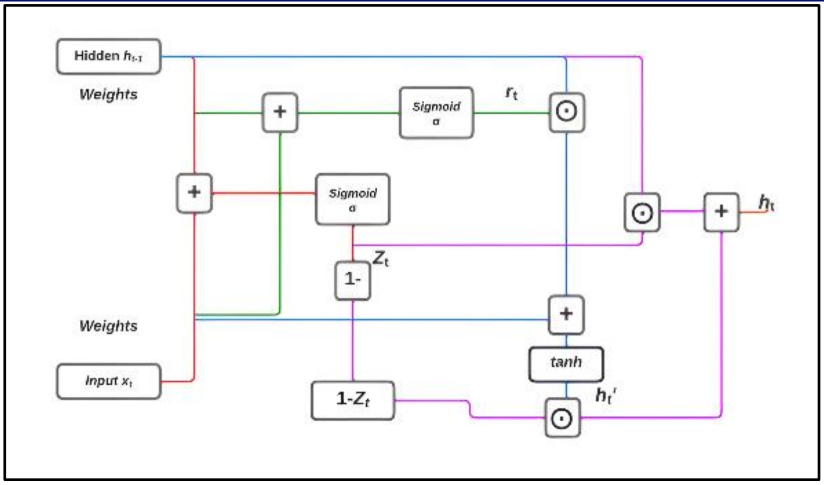

Figure 6. Gated Recurrent Unit Detailed Architecture

Reset gate: The reset gate, referred to as r_t, decides how much significance should be given to the previous information. It operates in a dissimilar manner compared to the update gate, possessing unique weights and implementation. The multiplication of two inputs, x_t and h_{t-1}, with corresponding weights in (4). The resultant values are then summed and subsequently passed through the sigmoid function [38].

$$r_t = sigmoid\ (W_r[h_{t-1}, x_t]) \tag{4}$$

Update gate: The purpose of update gate is to determine the amount of information required forward to next state [39]. The update gate z_t is involved as in (5), which expresses the multiplication of the input x_t and the output from the previous unit h_{t-1} with the weight W_z. The

$$z_t = sigmoid\ (W_z[h_{t-1}, x_t]) \tag{5}$$

output is constrained to a range of 0 to 1 with the *sigmoid* function.

3. Method

This section discusses the methodology for EOG artifact removal from the UCI EEG dataset using DWT and modified GRU approach for classification. It also provides a description of the publicly available UCI Machine Learning Repository dataset.

3.1 General Process for Epileptic Seizure Classification

Epileptic seizure classification in EEG involves several steps. First, electrical brain activity is recorded using EEG electrodes placed on the scalp. The data collected is then processed to remove any noise or artifacts, enhancing the signal quality. Next, relevant features are extracted from the preprocessed EEG signals, capturing patterns and characteristics associated with seizures. Using deep learning or classification algorithms, the EEG signals are categorized as either epileptic seizure or normal seizure types based on these selected features. The performance of the

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classification model is evaluated using various metrics such as accuracy, precision, recall, and F1 score. If necessary, the model is optimized and refined. This iterative process aims to achieve precise and reliable classification of seizures in EEG recordings, which in turn helps in diagnosing and treating epilepsy. Figure 7 illustrates the general process of epileptic seizure classification.

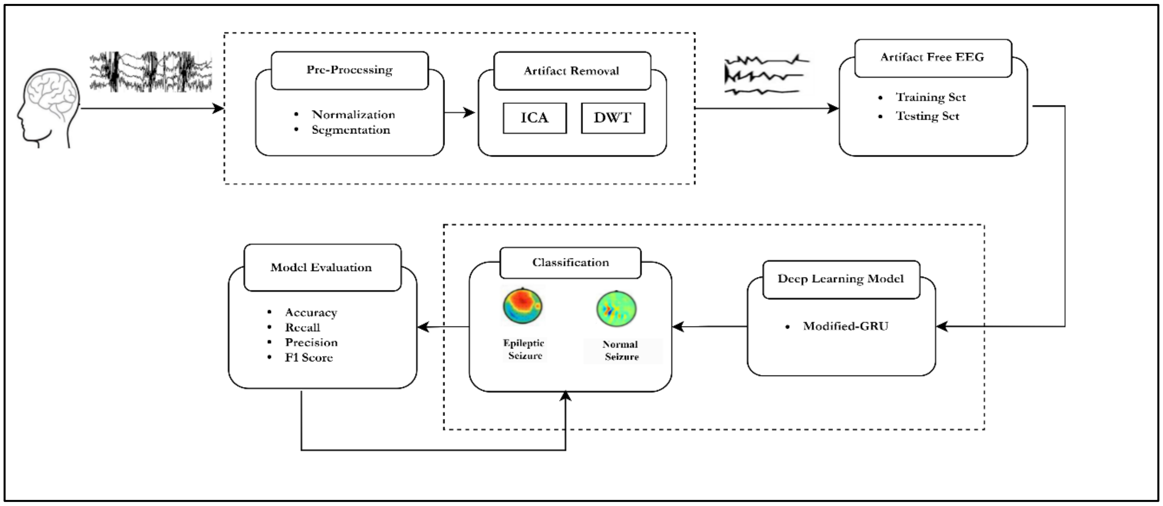

Figure 7. General Process for Seizure Classification

3.2 Dataset Description

The experiments utilized a dataset for epileptic seizure detection acquired from the UCI Machine Learning Repository, a publicly available database. Andrzejak et al. [40] provided an in-depth characterization of this dataset. The dataset has been pre-processed using DWT with an optimal daubechies wavelet (db7) and restructured for epileptic seizure identification. Table 1 displays the five subset classes of patients. Each subset comprises 100 single-channel EEG segments lasting 23.6 seconds.

Table 1. UCI Machine Learning Repository Dataset Description

Class	Class Description	Patient state	Cases
1	Eyes opened	Healthy	2300
2	Eyes closed	Healthy	2300
3	EEG (healthy area)	Partial Epilepsy	2300
4	EEG (tumour identified area)	Partial Epilepsy	2300
5	EEG (Seizure activity)	Epilepsy with seizure	2300

4. Results

The evaluation of the results was performed on both versions of the dataset. Initially, the experiment was carried out using an EEG dataset that was contaminated with artifacts. The results depicted in Table 2 that indicates with three phases of training, testing and validation of results. Table 3 illustrated the parameter results on EEG dataset after EOG artifact removal. The EEG dataset was cleaned with DWT approach after selection of optimal wavelet. Table 2 illustrates the performance of a Modified GRU model on an EEG dataset containing artifacts. It obtained the accuracy of 98.8% , precision 96.9% and 97.1% recall on the test data set.

Table 1. Modified GRU with Contaminated EEG Dataset

EEG Dataset	**Acc. (%)**	**Pre. (%)**	**Recall (%)**	**F1-Score (%)**
Training	97.5	95.4	97.6	96.5
Test	98.8	96.9	97.1	97
Validation	96.8	95.2	97.1	96.5

Table 2. Modified GRU with Artifact-Free EEG Dataset

EEG Dataset	**Acc. (%)**	**Pre.(%)**	**Recall (%)**	**F1-Score (%)**
Training	99.2	97.9	99.5	98.7
Test	99.5	97.4	97.8	97.6
Validation	98.8	97.6	99.2	98.7

Table 4 presents the performance of a Modified-GRU model on two classes of EEG data: Class 0 (with artifacts) and Class 1 (artifacts-free). The Modified-GRU model achieves high performance on both classes of data, with accuracy scores above 98% and F1-scores above 97%. However, the model performs slightly better on the artifacts-free data, with accuracy and F1-scores of 99.50% and 97.60%, respectively.

Table 3. Performance Metrices on Modified-GRU Classification Model

EEG Dataset	**Acc. (%)**	**Pre. (%)**	**Recall (%)**	**F1-Score (%)**
Class-0	98.8	96.9	97.1	97
Class-1	99.5	97.4	97.8	97.6

Where class-0 = Modified-GRU with contaminated EEG and class-1 = Modified-GRU with EOG Artifact Free EEG

Figure 10 represents a comparative analysis with modified GRU (M-GRU) methodology with the presence of artifact and subsequent to the elimination of EOG artifacts.

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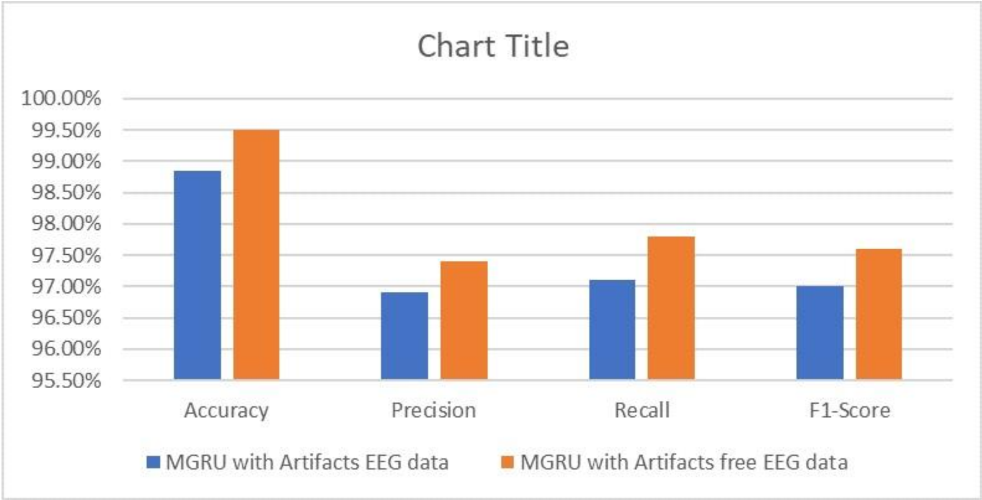

Figure 8. Comparative analysis of M-GRU with contaminated and Artifact-Free dataset

5. Discussion

The research work focuses on enhancing EEG signal analysis for epileptic seizure diagnosis by addressing the prevalent challenge of artifact contamination and utilizing advanced analytical techniques in hybrid approach for ocular artifact removal and deep learning to improve classification accuracy. The study begins by discussing the significance of EEG signals in clinical diagnosis and delves into the various types of artifacts that commonly disrupt these readings, evaluating existing denoising strategies to highlight their inadequacies. Subsequent efforts were directed towards a comprehensive literature review that scrutinizes past approaches to EEG denoising and seizure classification, which lays the groundwork for the thesis by identifying the current gaps in research.

A novel denoising technique that integrate ICA and DWT to remove ocular artifacts and a newly enhanced deep learning model - a Modified Gated Recurrent Unit (MGRU) designed to overcome prevalent issues in seizure classification, such as slow convergence rates and low learning efficiency. The results of this empirical evaluation demonstrate the superiority of the new approaches, which not only enhance the purity of EEG signals post-artifact removal but also improve the accuracy and reliability of seizure classification outcomes. The cleaned EEG data leads to a notable increase in classification accuracy, attaining an impressive 99.50% compared to 98.84% with the existing M-GRU approach. The proposed method classification results show an accuracy of 99.5%. Fukumori et al. [43] claimed an accuracy of 90.2% with a neural network method, RNN. Pisano et al. [44] achieved 98.84% accuracy with CNN. Liu et al. [45] designed a model with an accuracy of 96% by using CNN, LSTM, and GRU. Further, Jaafar and Mohammadi [46] presented an LSTM-based model with 97.75% accuracy. Two other models, 1D-CNN, LSTM, and GRU, were proposed by Chen et al. [11] and Acharya et al. [47] with 96.82% accuracy with GRU and 88.67% accuracy with CNN, respectively. The comparative analysis with other DL models is depicts in Figure11.

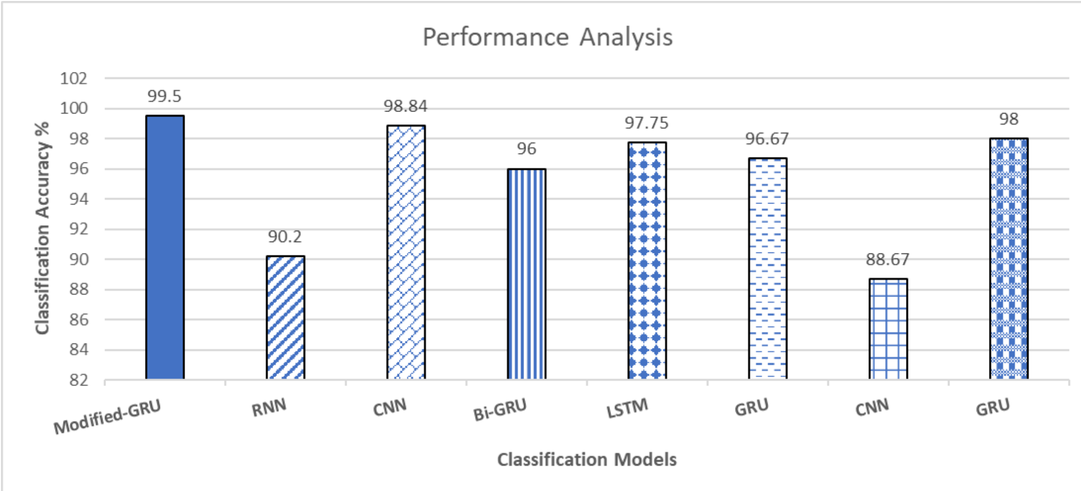

Figure 9. A Comparative Analysis of Existing DL Methods For Seizure Classification

6. Conclusions & Future directions

Electroencephalography or EEG is a technique routinely used for recording the natural electrical impulses and functioning of the brain over time. This non-invasive method offers various advantages, including affordability, widespread availability, and precise timing of brain activity. These signals are mostly contaminated with artifacts such as ocular, muscle and due to body movement or some external environmental interferences. This article discusses the use of the Discrete Wavelet Transform (DWT) approach, with the optimal 'db7' wavelet family, for removing ocular (EOG) artifacts from EEG datasets. In addition to that, we also applied a deep learning model known as a modified GRU to classify seizure patterns within the EEG signals—distinguishing whether they were epileptic or normal. The results were assessed on two different types of EEG sets—those with artifacts and those with cleaned signals. The findings showed that clean data produced superior results in terms of accuracy, precision, recall, and F1-score for the Modified GRU model. In summary, through pre-processing elimination of artifacts enables the identical model to attain superior outcomes, highlighting the importance of artifact removal for electroencephalography-based classification. The proposed Modified-GRU model is capable of learning robust EEG features. This indicates that the model has the potential to develop accurate and reliable EEG-based BCIs in real-world settings. In the conclusion section, The authors should explicitly write down the manuscript's contribution based on the results to answer the research questions. The conclusion contains a summary of what is learned from the results obtained, what needs to be improved in further study. Other common features of the conclusions are the benefits and applications of the research, limitation, and the recommendations based on the results obtained.

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