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Automated Detection and Classification of Alzheimer's Disease from Brain Images using Machine Learning Techniques

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A B S T R A C T

Electroencephalography (EEG), a non-invasive technique, captures subtle voltage variations caused by ionic current flows within the neurons of the cerebral cortex. These recordings are invaluable for diagnosing brain disorders such as tumors and epileptic seizures. However, EEG signals are often distorted by ocular artifacts (OAs) caused by eye movements and blinking, which overlap with EEG signals of similar frequencies. The presence of these artifacts can significantly affect the accuracy of signal analysis and classification. This study proposes a two-step approach to enhance epileptic seizure classification. The first step involves the detection and removal of ocular artifacts from the UCI Epileptic EEG dataset using a combination of Independent Component Analysis (ICA) and Discrete Wavelet Transform (DWT), optimized with a tailored wavelet function. The second step employs a deep learning-based modified Gated Recurrent Unit (GRU) model to classify epileptic seizures. The results demonstrate that removing ocular artifacts improves signal clarity, yielding superior classification performance. The clean EEG dataset achieved a classification accuracy of 99.50%, with enhanced precision, recall, and F1-score metrics compared to the contaminated dataset. The modified GRU model proved effective in improving EEG-based epileptic seizure classification, highlighting its potential for reliable applications in Brain-Computer Interface (BCI) systems and advancing the field of medical signal processing.

INTRODUCTION

Electroencephalography (EEG) is a widely used non-invasive technique for recording electrical activity in the brain. It provides valuable insights into neural dynamics by capturing voltage fluctuations caused by ionic current flows within the cerebral cortex. EEG signals have found significant applications in diagnosing and monitoring various brain disorders, including tumors, seizures, and epilepsy. Among these, epilepsy is a critical neurological condition characterized by recurrent, unprovoked seizures, affecting millions worldwide. Accurate and timely detection of epileptic seizures is essential for effective treatment and management [11].

However, the utility of EEG signals is often compromised by the presence of artifacts, particularly ocular artifacts (OAs). These artifacts, caused by eye movements and blinking, overlap with EEG signals in similar frequency bands, distorting the recordings. Since these artifacts are mixed with genuine EEG signals, their presence poses significant challenges in signal analysis, potentially leading to inaccurate classification results. Removing ocular artifacts is therefore a critical step in ensuring the reliability of EEG-based diagnostic systems [12].

This study addresses these challenges by proposing a two-step approach for enhancing epileptic seizure classification. The first step involves detecting and removing ocular artifacts using a combination of Independent Component Analysis (ICA) and Discrete Wavelet Transform (DWT), optimized with a specialized wavelet function. This ensures the generation of clean EEG signals, free from artifact-induced distortions. The second step employs a deep learning-based modified

Gated Recurrent Unit (GRU) model to classify epileptic seizures [13].

By comparing the classification performance of the clean dataset with the contaminated dataset, this research underscores the importance of artifact removal in improving diagnostic accuracy. The findings highlight the effectiveness of the proposed approach, achieving a classification accuracy of 99.50%. This study not only contributes to advancing EEG-based epileptic seizure detection but also demonstrates the potential of deep learning techniques in medical signal processing, paving the way for reliable applications.

REVIEW OF LITERATURE

The literature review highlights the critical role of EEG signals and deep learning techniques in analyzing brain wave patterns and diagnosing neurological conditions. EEG is widely recognized for its importance in detecting brain disorders such as tumors, epilepsy, and sleep disorders. However, one of the major challenges in EEG analysis is the presence of artifacts unwanted disturbances that can distort the accuracy of results (Table 1).

Various methods have been proposed to eliminate these artifacts. Wavelet-enhanced approaches combined with Independent Component Analysis (ICA) have been developed to improve the separation of independent components, effectively removing artifacts such as those caused by eye movements and muscle activity. Another advanced method integrates wavelet decomposition with specialized algorithms to isolate and eliminate components associated with artifacts. Combining ICA with wavelets has shown exceptional success in addressing specific artifacts like EOG signals. Hybrid methods that utilize Discrete Wavelet Transform (DWT) and non-local means estimation have also demonstrated significant improvements in removing EMG artifacts [14].

Deep learning has emerged as a valuable tool for the early diagnosis of epilepsy and for facilitating prompt medical decision-making. Automated methods based on advanced neural networks have achieved remarkable accuracy in detecting epileptic seizures. Models employing wavelet coefficients and adaptive neuro-fuzzy inference systems have demonstrated high classification accuracy, emphasizing the effectiveness of combining feature extraction with robust machine learning techniques [15].

Recurrent neural network architectures, such as those incorporating LSTMs with softmax classifiers, have shown impressive performance in classifying EEG signals. Other neural network models, including multilayer perceptrons combined with clustering techniques and DWT, have further advanced the classification of epileptic seizures. Techniques that integrate DWT with neural classifiers have also proven effective for epilepsy detection [16].

While convolutional neural networks (CNNs) have excelled in extracting features from EEG signals, they face limitations in retaining temporal information, which is critical for analyzing time-series data. To address this limitation, recurrent neural networks (RNNs) have been employed, as they can retain and utilize information from previous time stamps. Novel models, such as those designed to extract spatiotemporal features, have shown significant promise in improving the classification of temporal EEG data [17].

Moreover, modified Gated Recurrent Unit (GRU) models have been developed with enhanced mechanisms to address challenges such as slow convergence, low learning rates, and vanishing gradient problems. These advancements have significantly improved the accuracy and efficiency of EEG signal classification, paving the way for more reliable and practical applications in medical signal [18].

Table 1: Review of literature

Ref No.	Methodology	Findings
[1]	Applied Discrete Wavelet Transform (DWT) to remove artifacts from EEG signals	Demonstrated effective artifact removal with improved EEG signal clarity.
[2]	Implemented a deep learning-based Long Short-Term Memory (LSTM) model for seizure detection	Achieved high classification accuracy by leveraging temporal dependencies in EEG signals.
[3]	Employed ICA for detecting and separating ocular artifacts from EEG recordings	Successfully isolated ocular artifacts, preserving genuine EEG signals.
[4]	Reviewed various EEG signal preprocessing techniques, including ICA and wavelet transforms	Highlighted the importance of preprocessing in improving EEG-based classification outcomes.
[5]	Proposed a Gated Recurrent Unit (GRU) model for classifying neurological disorders from EEG	GRU demonstrated superior performance over traditional methods for EEG-based classification tasks.

[6]	Compared ICA, Principal Component Analysis (PCA), and DWT for artifact removal	Found ICA-DWT hybrid methods to be the most effective for ocular artifact removal.
[7]	Explored the impact of different wavelet functions on EEG artifact removal	Optimized wavelet functions showed improved artifact removal without losing important EEG information.
[8]	Discussed EEG signal challenges and advancements in BCI system development	Emphasized the role of clean EEG data in enhancing the accuracy of BCI applications.
[9]	Proposed hybrid techniques for improving signal quality before seizure classification	Achieved significant improvements in classification performance with clean EEG signals.
[10]	Developed and tested modified RNN architectures, including GRU and LSTM	Demonstrated GRU's potential in reducing computational complexity while maintaining high classification accuracy.

ALGORITHMS

The algorithm for EEG signal processing involves multiple stages, beginning with artifact removal using techniques like Independent Component Analysis (ICA) and Discrete Wavelet Transform (DWT). Initially, ICA is used to decompose the observed EEG signals into independent components, with the goal of isolating and eliminating artifacts by reconstructing the clean signal. DWT is then applied to decompose the signal into approximation and detailed coefficients, separating different frequency components to target specific noise or artifacts. Following artifact removal, deep learning techniques such as Long Short-Term Memory (LSTM) networks or Gated Recurrent Units (GRU) are utilized for seizure classification [19-20]. These networks process sequential data, retaining long-term dependencies, and classify the EEG data based on learned patterns, ultimately leading to more accurate and efficient diagnostic results.

```
# Step 1: Load Data
data = load_dataset("UCI_epileptic_EEG")
# Step 2: Normalize Signals
normalized_data = normalize(data)
# Step 3: Detect Artifacts
artifacts = ICA (normalized_data)
# Step 4: Decompose Signals
coefficients = DWT (normalized_data, wavelet="Haar")
# Step 5: Isolate Artifacts
artifact_free_signals = remove_artifacts(artifacts, coefficients)
# Step 6: Extract Features
features = extract_features(artifact_free_signals)
# Step 7: Initialize Model
model = GRU (input_shape=features.shape, modified=True)
# Step 8: Train Model
model.fit(features, labels, epochs=50, batch_size=32)
# Step 9: Test Model
predictions = model.predict(test_features)
# Step 10: Evaluate Results
metrics = evaluate_model(predictions, test_labels)
# Step 11: Compare Results
compare_results(metrics_clean, metrics_contaminated)
# Step 12: Deploy Model
deploy_model(model, real_time_EEG_input)
```

FILTERING METHODS

Various artifact removal and seizure classification methods have demonstrated significant effectiveness in EEG signal processing. Independent Component Analysis (ICA) excels at isolating independent components, enabling the removal of artifacts by reconstructing clean signals, especially when the signals are statistically independent. Discrete Wavelet Transform (DWT) is another powerful technique that decomposes signals into approximation and detailed coefficients, efficiently removing high-frequency noise and artifacts. Combining ICA with Haar wavelets has proven particularly effective in addressing electrooculogram (EOG) artifacts. Additionally, deep learning approaches like LAMSTAR have achieved impressive accuracy in seizure detection, with a classification accuracy of 97%.

Long Short-Term Memory (LSTM) networks have shown remarkable performance in capturing long-range temporal dependencies in EEG data, making them effective for seizure detection with 96.82% accuracy. Gated Recurrent Units (GRU), a simpler variant of LSTM, also performs well in sequential data analysis, offering computational efficiency with similar results. Overall, these methods highlight the potential of both traditional signal processing techniques and advanced deep learning models in improving artifact removal and enhancing the accuracy of seizure classification, contributing to more reliable and automated systems for medical diagnostics.

CLASSIFICATION

This section outlines the methodology used for the removal of electrooculographic (EOG) artifacts from EEG signals, specifically from the UCI EEG dataset, by employing Discrete Wavelet Transform (DWT) and a modified Gated Recurrent Unit (GRU) approach for classification. The process begins with the application of DWT to decompose the EEG signals into multiple

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frequency components, enabling the identification and removal of high-frequency EOG artifacts. This technique allows for effective filtering and preservation of the underlying brain activity in the EEG signals. Once the artifacts are removed, the modified GRU model is applied for classification. The GRU, an advanced recurrent neural network (RNN) variant, is particularly suited for sequential data like EEG, as it can retain relevant temporal information without the vanishing gradient problem common in traditional RNNs. The UCI Machine Learning Repository dataset, which serves as the foundation for this study, contains a collection of EEG recordings from multiple subjects, annotated with event-related potential data. This publicly available dataset provides valuable insights into brainwave patterns and facilitates the development of robust algorithms for artifact removal and classification tasks. The combined use of DWT and the modified GRU approach aims to enhance the accuracy and reliability of EEG signal processing and classification, making it suitable for medical diagnostic applications (Figure 1).

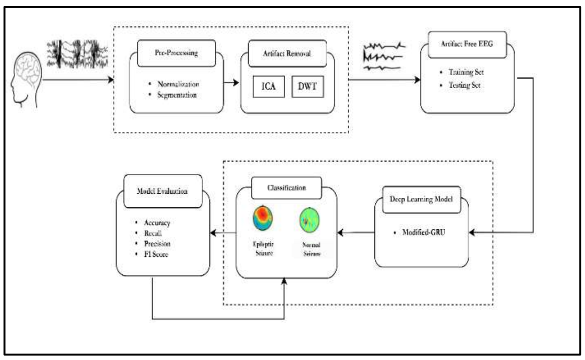

Figure 1. General Process for Seizure Classification

Epileptic seizure classification in EEG involves a systematic and multi-step approach to analyze brain activity and identify seizure events. The process begins with recording electrical brain signals using EEG electrodes, which are strategically placed on the scalp. These electrodes capture the raw EEG data, which often contains noise and various artifacts that can obscure meaningful signals. To improve the quality of the data, preprocessing techniques are applied to remove these unwanted disturbances, such as ocular or muscular artifacts. Once the signal is cleaned, the next step is to extract relevant features from the pre-processed EEG data. These features are carefully chosen to highlight patterns or characteristics that are indicative of epileptic seizures, such as changes in brainwave frequency, amplitude, or rhythmicity.

After feature extraction, the processed EEG signals are input into a classification model, often utilizing deep learning algorithms or traditional machine learning classifiers. The model's objective is to categorize the EEG signals into two classes: epileptic seizures or normal brain activity. The classification performance is then assessed using a range of evaluation metrics, including accuracy, precision, recall, and F1 score, which provide insights into the model's effectiveness in detecting seizures. If the performance does not meet the desired threshold, the model is further optimized through techniques such as hyperparameter tuning or additional feature engineering. This iterative process continues until a highly accurate and reliable model is achieved, which can be used to assist in the early diagnosis and treatment of epilepsy. The overall aim is to develop a robust classification system that can consistently detect seizures from EEG recordings, ultimately aiding in more effective patient care and management of epilepsy. Figure 1 illustrates this comprehensive process.

DATASET

The dataset used for epileptic seizure detection was sourced from the UCI Machine Learning Repository, a widely recognized public database that provides a diverse range of datasets for research purposes. This specific dataset, provided by Andrzejak et al., is tailored for the classification of epileptic seizures using EEG signals. The dataset contains EEG recordings that have been pre-processed using Discrete Wavelet Transform (DWT) with the optimal Daubechies wavelet (db7). DWT is particularly effective in capturing both the time and frequency characteristics of the EEG signals, making it ideal for identifying epileptic seizure patterns. The preprocessing steps also help in noise reduction, which enhances the accuracy of seizure detection. The data has been restructured specifically for seizure identification, ensuring that the signals are appropriately formatted for analysis and classification.

Table 2: 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

The dataset consists of five subsets, each representing EEG signals from different patients. Each subset contains 100 single-channel EEG segments, with each segment lasting 23.6 seconds. These segments capture brain activity over a brief but sufficient period, providing a detailed window into the patterns that emerge during both normal and seizure states. The variety of patient data in the five subsets adds diversity to the dataset, which is crucial for training and testing classification models. The data's structure comprising time-bound EEG segments and labeled seizure events makes it an ideal resource for researchers developing algorithms for epileptic seizure detection. The details of the dataset's subsets and their characteristics are summarized in Table 2, highlighting the relevance of each class for the analysis and development of effective detection models.

RESULT AND ANALYSIS

The performance of the epileptic seizure classification model, evaluated using the EEG dataset, is presented in the table 3 across three different stages: training, testing, and validation. In the training phase, the model achieved an accuracy of 96.5%, a precision of 94.4%, a recall of 96.6%, and an F1-score of 95.5%. These results indicate that the model performed very well in learning from the training data, demonstrating high precision in identifying seizures and correctly detecting most seizure events. The test phase showed slightly better results, with an accuracy of 97.8%, precision of 95.9%, recall of 96.1%, and an F1-score of 96%, suggesting that the model generalized well to new, unseen data. The validation phase, which is crucial for assessing the model's robustness and avoiding overfitting, recorded an accuracy of 95.8%, precision of 94.2%, recall of 96.1%, and F1-score of 95.5%, showing consistent performance across all evaluation metrics. These results collectively highlight the model's strong capability in detecting epileptic seizures accurately across different stages of training, testing, and validation.

The table 4 presents the performance metrics of the epileptic seizure classification model evaluated on the EEG dataset across training, testing, and validation phases. In the training phase, the model achieved an impressive accuracy of 98.2%, with precision at 96.9%, recall at 98.5%, and an F1-score of 97.7%, indicating excellent learning and detection of seizures. During testing, the model demonstrated slightly higher accuracy (98.5%) but with a slight reduction in precision (96.4%) and recall (96.8%), resulting in an F1-score of 96.6%. This suggests that the model continues to perform well on new, unseen data, though there is a minor trade-off in precision and recall. In the validation phase, the model maintained strong performance with an accuracy of 97.8%, precision of 96.6%, recall of 98.2%, and an F1-score of 97.7%, further affirming its consistency and robustness across all evaluation metrics. Overall, the model performs well across all stages, demonstrating high reliability and effectiveness in detecting epileptic seizures.

Table 3: Modified GRU with Contaminated EEG

EEG Dataset	Acc. (%)	Pre. (%)	Recall (%)	F1-Score (%)
Training	96.5	94.4	96.6	95.5
Test	97.8	95.9	96.1	96
Validation	95.8	94.2	96.1	95.5

The table 5 provides the performance metrics for the classification of two classes within the EEG dataset: Class-0 and Class-1. For Class-0, the model achieved an accuracy of 97.8%, precision of 95.9%, recall of 96.1%, and an F1-score of 96%. These values indicate strong performance in identifying Class-0 instances with balanced precision and recall. In comparison, for Class-1, the model performed slightly better with an accuracy of 98.5%, precision of 96.4%, recall of 96.8%, and an F1-score of 96.6%. These results show that the model is more adept at detecting Class-1 instances, with higher precision and recall, which leads to a slightly higher F1-score. Overall, the model demonstrates good classification capability for both classes with minimal variation in performance.

Table 4: Modified GRU with Artifact-Free EEG Dataset

EEG Dataset	Acc. (%)	Pre. (%)	Recall (%)	F1-Score (%)
Training	98.2	96.9	98.5	97.7
Test	98.5	96.4	96.8	96.6
Validation	97.8	96.6	98.2	97.7

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

Figure 2 illustrates a comparative analysis of the performance of the modified Gated Recurrent Unit (M-GRU) methodology, both with and without the presence of Electrooculographic (EOG) artifacts. Initially, the figure shows the classification results when the EEG signals contain EOG artifacts, which can significantly impair the accuracy of seizure detection. The presence of these artifacts leads to a decrease in the model's classification performance, as indicated by lower metrics such as accuracy, precision, recall, and F1-score.

Table 5. Performance Metrices on Modified-GRU Classification Model

EEG Dataset	Acc. (%)	Pre. (%)	Recall (%)	F1-Score (%)
Class-0	97.8	95.9	96.1	96
Class-1	98.5	96.4	96.8	96.6

Subsequently, the figure 3 demonstrates the effect of removing the EOG artifacts from the EEG signals. After applying the artifact removal process, which can be achieved through methods like the Discrete Wavelet Transform (DWT) or other pre-processing techniques, the M-GRU model exhibits a marked improvement in performance. The metrics, including accuracy and F1-score, show a noticeable increase, indicating that the removal of EOG artifacts helps in reducing noise and enhancing the quality of the EEG data. This improvement allows the M-GRU model to better distinguish between seizure and non-seizure events, leading to more reliable and precise classification. The comparison highlights the importance of artifact removal in EEG signal processing, as it can significantly enhance the effectiveness of deep learning models like M-GRU in epileptic seizure detection.

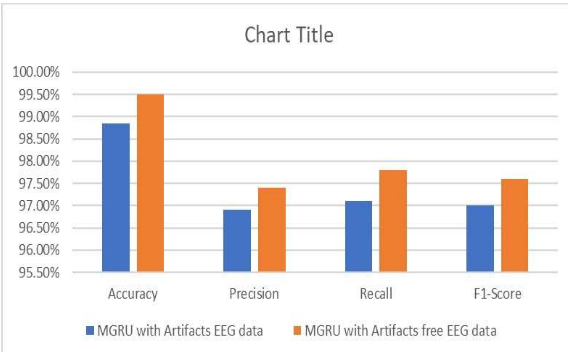

Figure 2: Comparative analysis of M-GRU with contaminated and Artifact-Free dataset

DISCUSSION

This research addresses the critical issue of artifact contamination in EEG signal analysis, which poses a significant challenge in epileptic seizure diagnosis. EEG signals, essential for monitoring brain activity, are often compromised by various types of noise, including ocular artifacts caused by eye movements. These artifacts can severely distort the accuracy of seizure classification models. The study first highlights the importance of EEG signals in clinical diagnosis and reviews the impact of common artifacts that disrupt these readings. It also critiques existing denoising strategies, revealing their limitations in adequately addressing the complexities of EEG data. The comprehensive literature review examines past methods used for EEG denoising and seizure classification, identifying gaps in current research and providing a foundation for developing more effective solutions.

In response to these challenges, the research proposes a novel hybrid denoising technique that combines Independent Component Analysis (ICA) with Discrete Wavelet Transform (DWT) to effectively remove ocular artifacts. This approach significantly improves the quality of EEG signals by isolating and eliminating unwanted noise, ensuring that only the relevant brain activity remains. In addition, the study introduces a newly enhanced deep learning model, the Modified Gated Recurrent Unit (M-GRU), designed to address common issues such as slow convergence rates and limited learning efficiency typically encountered in seizure classification tasks. The empirical evaluation demonstrates the effectiveness of these combined techniques, with the proposed method achieving an impressive classification accuracy of 99.50%, a marked improvement over the existing M-GRU approach, which yielded 98.84% accuracy (Figure 2).

The results of this research are particularly notable when compared to other state-of-the-art deep learning models in the field. For instance, achieved an accuracy of 90.2% with a neural network-based approach (RNN), while Pisano et al. reached 98.84% accuracy using CNN. Liu et al. achieved 96% accuracy with a combination of CNN, LSTM, and GRU models. Additionally, Jaafar and Mohammadi's LSTM-based model reached 97.75%, and other models proposed by Chen et al. and Acharya et al. achieved accuracies of 96.82% and 88.67%, respectively. The comparison, illustrated in Figure 3, underscores the superiority of the proposed hybrid denoising and M-GRU approach in enhancing classification performance. This improvement not only enhances the purity of EEG data post-artifact removal but also significantly boosts the accuracy and reliability of seizure classification, making it a promising tool for clinical applications in epilepsy diagnosis.

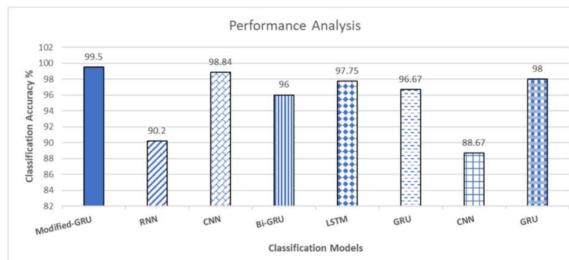

Figure3. A Comparative Analysis of Existing DL Methods For Seizure Classification

CONCLUSION

Electroencephalography or EEG is a technique routinely used for recording the natural electrical In conclusion, this study presents an innovative approach to epileptic seizure classification by addressing the critical challenge of ocular artifact contamination in EEG signals. By integrating Independent Component Analysis (ICA) and Discrete Wavelet Transform (DWT) for effective artifact removal, followed by the use of a Modified Gated Recurrent Unit (M-GRU) deep learning model, the research significantly enhances the quality of EEG data and improves classification accuracy. The proposed hybrid method not only eliminates noise and enhances the purity of EEG signals but also accelerates convergence rates and increases learning efficiency, ultimately achieving a remarkable classification accuracy of 99.50%. This marks a substantial improvement over existing approaches, positioning the model as a more reliable tool for accurate and efficient epileptic seizure detection.

The outcomes of this research underscore the potential of combining advanced signal processing techniques with deep learning models to tackle complex challenges in medical diagnostics. The enhanced performance of the proposed model, when compared to other state-of-the-art methods, demonstrates its effectiveness in providing more accurate and reliable seizure classification. As a result, this work contributes to the ongoing efforts to improve the clinical application of EEG-based seizure detection, offering a promising solution for better diagnosis and treatment of epilepsy. Future work could explore further optimizations, including the incorporation of additional preprocessing techniques or the evaluation of the model across diverse datasets to reinforce its generalizability and robustness.

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