

Feature Fusion Based MCI Detection on Time-Domain and Deep Features Using EEG Signals

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Electroencephalogram (EEG) signal analysis is an important tool for diagnosing and monitoring neurological disorders. This study introduces a new method for classifying EEG signals using a combination of time-domain features and Recurrent Neural Network (RNN). The dataset includes EEG recordings from both Healthy Control and Mild Cognitive Impairment patients information. The data is cleaned to remove noise and divided into fixed-length segments. Time-domain features, such as Hjorth parameters, Kurtosis, and Zero-Crossing Rate (ZCR), are extracted from each segment. At the same time, the RNN model captures the temporal patterns in the signal.

A hybrid feature extraction method named "Deep Temporal Feature Integration" (DTFI) is used. This method combines time-domain features with those of the RNN features and includes an attention mechanism to enhance feature weighting. The combined features train a classifier, which achieves a high accuracy of 97.75% on the test set. The results show that the fused features significantly improve classification performance compared to using individual features alone. This study demonstrates the potential of hybrid feature extraction techniques and advanced neural network models in improving EEG signal classification accuracy, which can be beneficial for clinical applications.

Keywords: Electroencephalography (EEG); Mild Cognitive Impairment (MCI); Healthy Control (HC); Recurrent Neural Networks (RNN), DTFI (Deep Temporal Feature Integration).

1. Introduction

Mild Cognitive Impairment (MCI) is a condition characterized by a noticeable decline in cognitive abilities, including memory and thinking skills, which is more severe than normal age-related changes but not as severe as those seen in dementia. MCI serves as an intermediate stage between the cognitive decline of normal aging and more serious conditions like Alzheimer's disease [1]. Patients with MCI are at an elevated risk of developing Alzheimer's disease or other dementias, making early detection and diagnosis crucial for managing and potentially mitigating the progression of cognitive decline [2].

Electroencephalogram (EEG) has emerged as a valuable tool for non-invasive monitoring of brain activity and has been increasingly used in the detection of MCI. EEG signals capture the electrical activity generated by neuronal firing in the brain and provide a wealth of information about brain function. Studies have shown that EEG features, such as the slowing of alpha rhythms, can serve as biomarkers for MCI and predict the progression to Alzheimer's disease [3]. EEG signals are typically collected using electrodes placed on the scalp, following standardized protocols like the International 10-20 system, which ensures consistent and reproducible measurements [4].

The analysis of EEG signals for MCI detection has traditionally relied on the extraction of specific features from the EEG data, including time-domain features, frequency-domain features, and time-frequency features. Time-domain features provide insights into the signal's amplitude and frequency characteristics. For instance, Hjorth parameters, which encompass activity, mobility, and complexity, describe the signal's temporal structure [5]. The Zero-Crossing Rate (ZCR), another important time-domain feature, measures the rate at which the signal changes polarity, reflecting the signal's frequency content [6].

Frequency-domain features, obtained through methods like the Fourier Transform, decompose EEG signals into their constituent frequencies, allowing for the identification of dominant frequency bands that may be indicative of cognitive decline [7]. Time-frequency features derived from the Wavelet Transform offer a more comprehensive view by capturing both the temporal and spectral characteristics of the EEG signals, making them particularly useful for detecting transient features associated with MCI [8].

While these traditional methods have provided valuable insights into EEG signal analysis, they often require substantial domain knowledge and manual feature extraction, which can be time-consuming and may not capture all relevant patterns in the data. To address these limitations, advanced neural network approaches have gained prominence in recent years. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated significant promise in automating feature extraction and improving classification accuracy in EEG signal analysis.

CNNs are highly effective in capturing spatial features from EEG signals, learning relevant patterns directly from the raw data without the need for manual feature engineering. This has led to superior performance in EEG classification tasks compared to traditional methods [9]. On the other hand, RNNs, including Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), are particularly suited for processing sequential data, such as EEG signals, due to their ability to capture temporal dependencies. RNNs have been successfully applied to detect patterns in EEG data that are indicative of neurological events, such as seizures, and are increasingly being used for MCI detection [10].

CNNs have been effectively utilized to classify EEG-based cognitive tasks by automatically extracting and learning patterns directly from the raw data, which has significantly advanced the potential of deep learning in cognitive analysis [11]. Similarly, deep CNNs have been developed to decode EEG and MEG signals, achieving superior performance and demonstrating their applicability in neurological research [12]. In clinical applications, deep learning frameworks have been successfully employed for automatic seizure detection, further validating the efficacy of these methods in practical settings [13].

In the context of hybrid models, combining CNNs with RNNs has proven particularly advantageous for EEG-based MCI detection. By first utilizing CNN layers to extract spatial features, followed by RNN layers to capture temporal dependencies, these hybrid models have significantly improved classification performance [14]. Additionally, the robustness and versatility of such hybrid deep learning models have been highlighted in EEG-based emotion recognition tasks, further demonstrating their broad applicability across different EEG signal classification challenges [15].

The main objectives of this research are to analyze multi-channel EEG signals for classifying healthy individuals and MCI patients using a hybrid feature fusion method called "Deep Temporal Feature Integration" (DTFI). The steps are as follows:

1. The raw EEG signals are collected from the Isfahan MISP database, which includes data on healthy controls (HC) and patients with mild cognitive impairment (MCI).
2. Preprocessing is applied with common average referencing, bandpass filtering to remove noise, and the signals are divided into smaller epochs for better signal quality.
3. Time-domain features like Hjorth parameters, Kurtosis, and Zero-Crossing Rate (ZCR) are extracted from the preprocessed EEG signals to capture their essential characteristics and spatial information.
4. Deep learning features from Recurrent Neural Network (RNN) are extracted to identify temporal patterns and dependencies in the EEG signals.
5. The Deep Temporal Feature Integration (DTFI) method is applied on time-domain features and RNN-derived features.
6. Train a shallow neural network with two hidden layers using the fused features to distinguish between HC and MCI patients.
7. Evaluate the classifier's accuracy and effectiveness using various performance metrics.

This study aims to advance the field of EEG signal analysis, providing more accurate diagnostic tools and contributing to better patient outcomes in clinical settings. The process flow diagram for MCI detection is shown in Fig. 1.

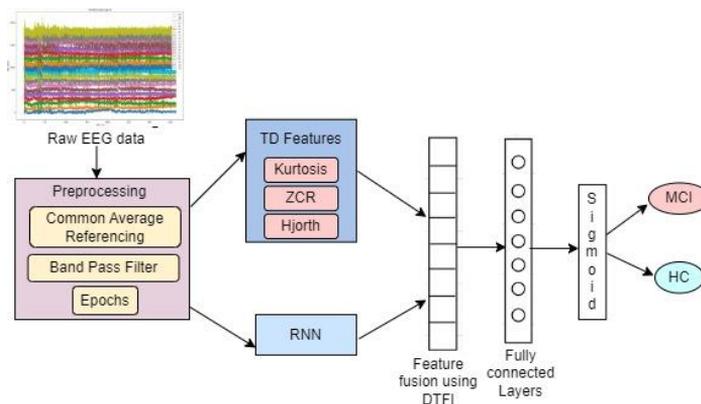


Fig 1. Process flow diagram of proposed feature fusion-based MCI detection.

Dataset Description

The study used EEG data from the Isfahan MISP database, which included 61 participants, all aged 55. These participants were divided into two groups: 29 healthy controls and 32 with mild cognitive impairment (MCI). EEG recordings were taken during morning sessions while the participants' eyes were closed, using a Galileo NT device with 19 electrodes based on the international 10-20 system. The electrodes included positions such as Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2. The data was captured using a 32-channel digital EEG device with a sampling rate of 256 Hz and was saved in EDF format [16-17].

Methods

3.1 Preprocessing Techniques

EEG signals are often contaminated with various types of noise and artifacts, including muscle movements, eye blinks, and electrical interference. Preprocessing helps in cleaning these signals to better reflect the underlying brain activity. According to [18], preprocessing can enhance the signal-to-noise ratio (SNR), making the signals more interpretable and reliable for analysis. Another study by [19] emphasizes that proper preprocessing is essential for reducing false positives and improving the accuracy of EEG-based diagnostics

In the preprocessing of EEG data for MCI detection, two critical techniques—common average referencing and band-pass filtering—are strategically employed to enhance signal quality and focus on relevant neurological information. Common average referencing is used to reduce shared noise across EEG channels, effectively enhancing the signal-to-noise ratio. This approach is particularly valuable in emphasizing genuine brain activity over environmental and equipment noise, thus improving the clarity and interpretability of the EEG data. Following this, a band-pass filter is applied, restricting the EEG signals to a frequency range of 0.5 to 45 Hz. This specific range is chosen to focus the analysis on frequencies that are most likely to reveal cognitive state changes associated with MCI, eliminating higher and lower frequencies that might contribute to noise or are less likely to be associated with cognitive functions.

The preprocessing also includes the segmentation of the continuous EEG signal into epochs, which is a fundamental step for structuring the analysis. This division into fixed-length segments of 5 seconds each, with an overlap of 1 second between consecutive epochs, is crucial because it allows for consistent and manageable analysis across all data samples. Overlapping epochs are often used to ensure that no data is missed and to capture continuous brain activity. Segmenting the data into epochs enables a focused examination of EEG readings over uniform time intervals, facilitating the identification of consistent or transient patterns that may indicate cognitive impairment. Each epoch serves as a discrete unit of brain activity, offering a clear view of temporal dynamics essential for effective feature extraction and subsequent analysis. The sample EEG signal for 1 minute duration is shown in Fig 2.

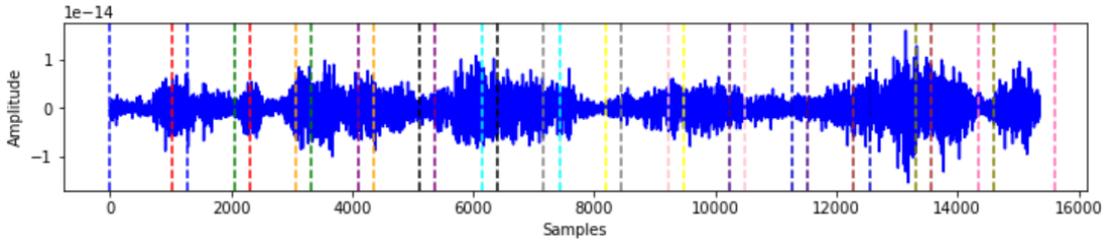


Fig 2. Sample EEG Signal shown for 1 minute.

3.2 Feature extraction techniques

Feature extraction is a crucial step in the analysis of EEG signals. It involves the transformation of raw EEG data into a set of features that can be more easily analyzed and interpreted. These features can reveal patterns and characteristics that are not immediately apparent in the raw data, thus facilitating more accurate classification and analysis.

3.2.1. Time domain Features

Time-domain features are integral to EEG signal analysis because they directly capture essential characteristics of the signal's amplitude and frequency, often without the need for transformation into other domains, such as frequency or time-frequency domains. These features are typically computationally efficient to extract, making them suitable for real-time analysis and applications where computational resources are limited. Among various time-domain features, Hjorth parameters, Kurtosis, and Zero-Crossing Rate (ZCR) stand out due to their unique capabilities to summarize and interpret the EEG data. These extracted features play a significant role in enhancing the performance of machine learning models applied to EEG data [20]. By utilizing appropriate feature extraction techniques, it becomes possible to better understand the underlying neural activity and improve the accuracy of diagnostic and classification tasks [21].

The Hjorth parameters like activity, mobility and complexity, were used on the preprocessed EEG signals, resulting in the extraction of 57 features per signal, with a total feature set dimension of (28,402, 57). Kurtosis, which measures the sharpness of the signal distribution and indicates how frequently extreme values occur, was applied to the same preprocessed signals, yielding 19 features per signal and a total feature set dimension of (28,402, 19). Additionally, the Zero Crossing Rate (ZCR), which measures how often the signal changes from positive to negative, was used on the preprocessed EEG signals, also resulting in 19 features per signal, with the total feature set dimension being (28,402, 19). The Time domain extraction process is shown in Fig 3.

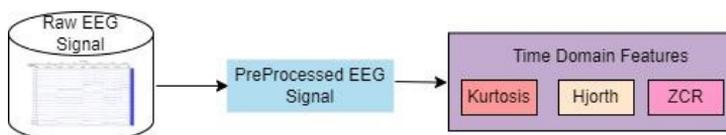


Fig 3. Process of Time Domain Feature Extraction

3.2.2. Deep Learning Features

Recurrent Neural Networks (RNNs) are uniquely designed to handle sequence prediction problems by processing data through sequences, making them ideal for time-series data such as EEG signals. Unlike feedforward neural networks, RNNs incorporate loops in their network structure that allow them to maintain a 'memory' of previous inputs. This capability enables them to capture dynamic temporal behavior, which is crucial for analyzing data where time context is essential, such as EEG [22].

In the context of detecting Mild Cognitive Impairment (MCI), RNNs are invaluable for their ability to capture temporal dependencies and subtle nuances in EEG data, which are indicative of neurological changes associated with MCI. These changes often manifest as slight alterations in brain activity patterns that might not be clearly apparent but can consistently appear over time, signaling the onset of cognitive decline. By recognizing these early signs, RNNs offer a significant advantage in identifying potential MCI cases that might be overlooked by less sensitive models [23].

For the specific task of detecting MCI using EEG signals, the deployed architecture utilizes a Simple RNN layer tailored for efficient feature extraction. This Simple RNN configuration includes 64 units with ReLU activation, enhancing its capability to discern complex patterns in the EEG data. The Simple RNN processes the EEG data sequentially, extracting essential temporal features by leveraging its memory capability to retain relevant information from previous inputs. This feature extraction is crucial as it transforms raw EEG data into a more analyzable form, focusing solely on capturing meaningful attributes that reflect underlying cognitive processes.

3.2.3. Feature Fusion of Time Domain and Deep Learning Features Using Deep Temporal Feature Integration (DTFI)

Dual Canonical Correlation Analysis (DCCA) is an advanced version of Canonical Correlation Analysis (CCA). While CCA identifies the relationships between two sets of variables by finding linear combinations that maximize their correlation, DCCA extends this by allowing for more complex interactions and handling multiple datasets simultaneously. DCCA is particularly important compared to traditional CCA because it can capture a broader range of dependencies and interactions between datasets, making it ideal for complex biological data such as EEG signals. This capability is crucial in scenarios where simple linear correlations do not sufficiently describe the relationships within the data, such as in neuroimaging where multiple brain regions and signal types may interact in intricate ways. The attention mechanism in neural networks is a technique that allows models to focus selectively on parts of the input data that are most relevant for the task at hand [24-25].

In medical diagnostics, particularly when identifying conditions such as Mild Cognitive Impairment (MCI) through EEG data, leveraging advanced technology is crucial. A key innovation in our research has been the adoption of the Deep Temporal Feature Integration (DTFI). This advanced model utilizes Dual Canonical Correlation Analysis (DCCA) integrated with an attention mechanism, effectively merging complex data types—specifically, time-domain signals and deep learning outputs from RNNs.

The process begins with DCCA, which combines input features from both the static time-

domain analyses and dynamic features extracted by RNNs. This initial step is vital as it synthesizes both static and dynamic aspects of EEG data into a unified feature set, providing a comprehensive view of brain activity that enriches our analytical capabilities. DCCA achieves this by leveraging a custom loss function known as the correlation loss. This loss function is designed to maximize the correlation between the transformed feature sets from both domains—Time domain features and RNN features. Specifically, the correlation loss is calculated by centering the data, computing the covariance between the two sets of transformed features, and then normalizing this covariance to obtain a correlation coefficient. By minimizing the negative of this correlation, the model ensures that the two feature sets are projected into a space where they are highly correlated, effectively fusing the diverse information into a single, coherent representation.

Following the fusion via DCCA, the DTFI model employs an attention mechanism to further refine these integrated features. The attention mechanism works by assigning a weight to each part of the fused feature set, which reflects its importance in the context of the task—in this case, detecting MCI. Imagine this as fine-tuning a camera lens to enhance image clarity—the model evaluates the fused features and focuses on those most crucial for accurately detecting MCI. This prioritization is immensely valuable in clinical environments, where distinguishing the most informative features can lead to earlier and more precise diagnoses. The attention mechanism amplifies the contribution of the most relevant features while diminishing the impact of less informative ones, thereby increasing the model's accuracy and reliability.

The strength of DTFI lies in its synthesis of traditional statistical methods with modern machine learning technologies. By merging these approaches, the model not only boosts our ability to fuse diverse data but also enhances the overall robustness and accuracy of our diagnostic tools. The DCCA component ensures that the feature fusion is both comprehensive and effective, capturing the full spectrum of relationships within the EEG data. Meanwhile, the attention mechanism fine-tunes this fused representation, ensuring that the most critical features are emphasized. This integrated method substantially surpasses traditional techniques that might use these analytical methods separately, showcasing how innovative combinations of technologies can advance medical diagnostics and lead to better clinical outcomes.

DTFI Algorithm steps:

- Pass the Time domain features and RNN features through separate neural networks to transform them into higher-dimensional feature spaces.
- Center the transformed feature sets by subtracting their mean values.
- Calculate the correlation between the centered Time domain and RNN feature sets.
- Define a custom loss function based on the negative correlation and minimize it to ensure the transformed feature sets are highly correlated.
- Concatenate the transformed and fused features from the Time domain and RNN domains to create a comprehensive feature set.
- Refine the fused feature set using an attention mechanism by assigning weights to each part of the fused feature set based on their relevance to the task.

- Multiply the fused features by the attention weights to enhance the most critical features while reducing the influence of less informative ones.
- Output the refined, fused features optimized for tasks such as detecting Mild Cognitive Impairment (MCI) from EEG data.

4. Experimental Results

For detecting Mild Cognitive Impairment (MCI), Python programming is utilized to handle and preprocess EEG data efficiently. The preprocessing workflow includes using the MNE package to load EEG files, set a standard reference, and apply a band-pass filter to isolate useful frequencies between 0.5 Hz and 45 Hz. The continuous EEG recordings are also segmented into five-second epochs with one-second overlaps, allowing for detailed analysis of the data in manageable chunks. For implementing RNN and Hybrid model Keras 2.0, and Tensor flow 1.4.0 are used.

5. Dataset

The study used EEG data from the Isfahan MISP database. Initially the raw EEG signals were preprocessed using common average referencing and Band pass filter with frequency range of 0.5 to 45 Hz. The preprocessed EEG signal with 19 channels is segmented into 5 second epochs with 1 second overlap. Each EEG signal is recorded for 30mins are more, resulting in a total of 28,402 segments. The experiment is carried out with 75% for training and 25% for testing from total of 28,402 segments. The sample EEG signals are shown in Fig 4. And Fig 5.

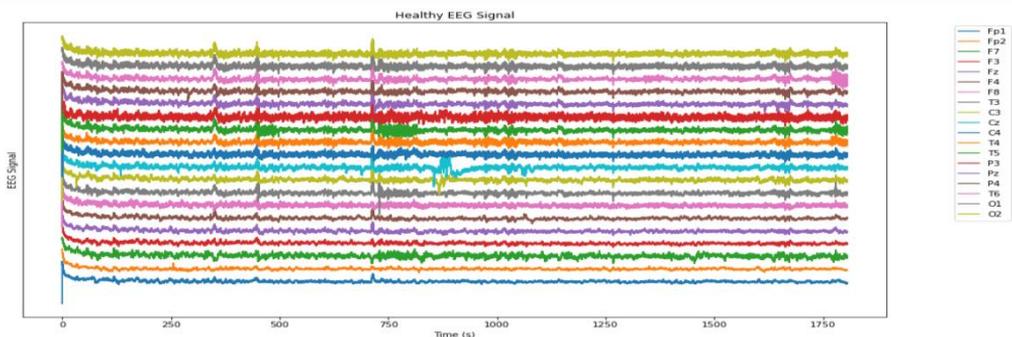


Fig 4. Sample EEG signals for Healthy Control

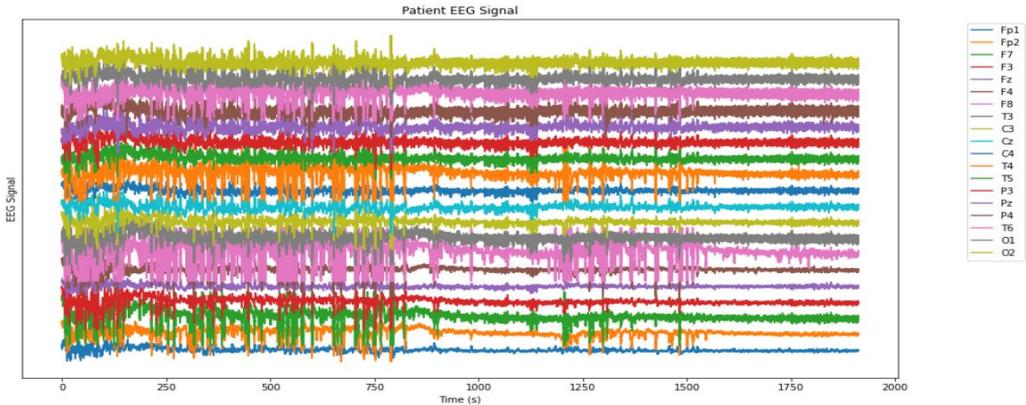


Fig 5. Sample EEG signals for Mild Cognitive Impairment

6. Performance metrics

Performance measures are metrics used to evaluate the effectiveness of a model or system, particularly in machine learning and data analysis. These measures help determine how well a model is performing in terms of predicting or classifying data. Understanding and correctly applying these metrics is crucial for assessing the quality and reliability of a model's predictions [26-27]. The confusion matrix is shown in Fig 6.

		Predicted Class	
		MCI	HC
Actual Class	MCI	TP True Positives	FN False Negatives
	HC	FP False Positives	TN True Negatives

Fig 6. Confusion Matrix for MCI and HC classification.

1. Accuracy: Accuracy is the ratio of correctly predicted instances to the total instances.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

2. Precision: Precision (also called Positive Predictive Value) is the ratio of correctly predicted positive observations to the total predicted positives.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

3. Recall: Recall (also called Sensitivity or True Positive Rate) is the ratio of correctly predicted positive observations to all observations in the actual positive class.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

4. **F1 Score:** The F1 Score is the harmonic mean of Precision and Recall. It provides a single metric that balances both the precision and recall and is especially useful when you need a balance between precision and recall.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

7. Feature Extraction

Time Domain Features

The time domain features are extracted using Hjorth parameters, kurtosis and ZCR . A total of 95 features are extracted which includes 57 hjorth features, 19 kurtosis features and 19 ZCR features, for all 19 channels for each EEG Segment.

RNN Parameters

The input EEG time series data has a specific shape defined by input_shape. It is processed through the RNN where the SimpleRNN layer is configured with 64 units, and the ReLU activation function is applied to introduce non-linearity and enhance model performance.

The static time domain features and the temporal features extracted by the RNN are integrated using DTFI. These features are then passed through the classification model with three dense layers. The first two dense layers have 64 and 32 units, respectively, with the ReLU activation function applied to both. Batch normalization is applied after each dense layer to stabilize the learning process. The final output layer uses a sigmoid activation function to perform binary classification.

8. Feature Fusion of Time-Frequency Features and Deep Learning

Time-domain features are extracted from each 5-second EEG segment across 19 channels, totaling 95 features per epoch, while the RNN extracts 64 deep learning features. A total of 159 features are fused using a Deep Temporal Feature Integration method (DTFI). After DTFI, the features are reduced to 100, and these feature vectors are fed into a shallow neural network comprising two fully connected layers with ReLU activation functions and a sigmoid activation function in the output layer to classify different classes.

Table 1 shows the confusion matrix and performance metrics of the feature fusion model for analyzing EEG signals to detect various classes using different optimizers. The experiments were conducted with a training dataset comprising 75% of the total data and a testing dataset comprising 25%. The performance of the feature fusion model, particularly when using the Adam optimizer, is good, with an accuracy of 97.75%.

Table 1: Performance metrics of feature fusion model for MCI detection with different optimizers

Optimizer		Accuracy		Performance Metrics in %			
		MCI	HC	Precision	Recall	F1score	Overall Accuracy
Adam	MCI	98.14	1.86	97.64	97.64	97.64	97.75

	HC	2.14	97.64	97.64	97.64	97.64	
RMSprop	MCI	98.18	1.18	96.32	98.18	97.24	97.05
	HC	4.10	95.90	95.90	95.90	95.90	
SGD	MCI	97.53	2.47	97.47	97.53	97.50	97.49
	HC	2.53	97.47	97.47	97.47	97.47	

When analysed with different optimizers for feature fusion model, the experimental results show that adam optimizer because of convergence speed and stability of the model training process, proved to achieve a highest accuracy of 97.75% when compared to others. Fig 7. shows the comparative analysis of feature fusion model with different optimizers for EEG signal analysis to classify MCI and HC.

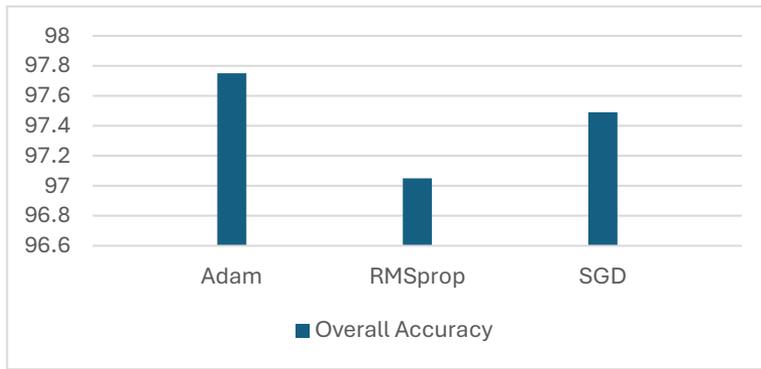


Fig 7. Feature fusion model with different optimizers.

In Fig 8, (a) shows the plot of accuracy of the model over the training and validation data, and (b) shows the plot of loss of the model over the training and validation data using the Adam optimizer. The training accuracy increases sharply initially and stabilizes close to 99% as the epochs progress, while the validation accuracy fluctuates and stabilizes around 97.7%. The training loss decreases rapidly and stabilizes at a low value, indicating good model fit, whereas the validation loss stabilizes after an initial drop and remains relatively constant over the epochs.

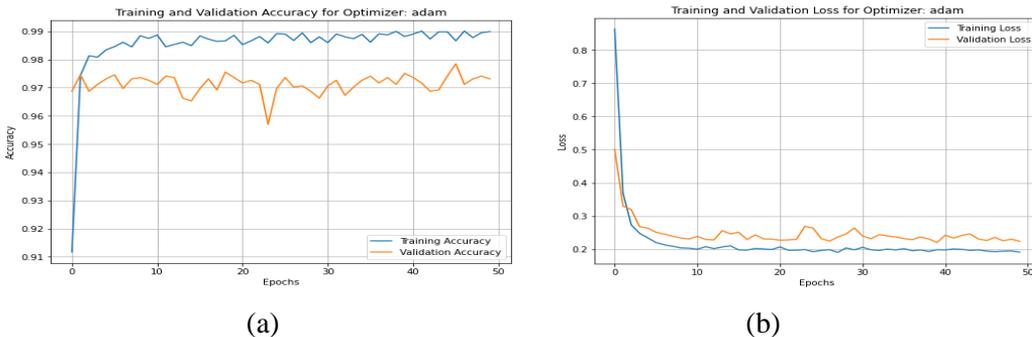


Fig 8. Feature fusion model with Adam optimizer

(a) Training - Validation Accuracy and (b) Training - Validation Loss.

In Fig 9, (a) shows the plot of accuracy of the model over the training and validation data, and (b) shows the plot of loss of the model over the training and validation data using the RMSprop

optimizer. The training accuracy rapidly increases and stabilizes close to 99%, while the validation accuracy remains relatively stable around 97.5% with minor fluctuations. The training loss decreases significantly and stabilizes at a low value, indicating effective learning by the model. The validation loss, after an initial drop, stabilizes with some fluctuations, maintaining a consistent pattern over the epochs.

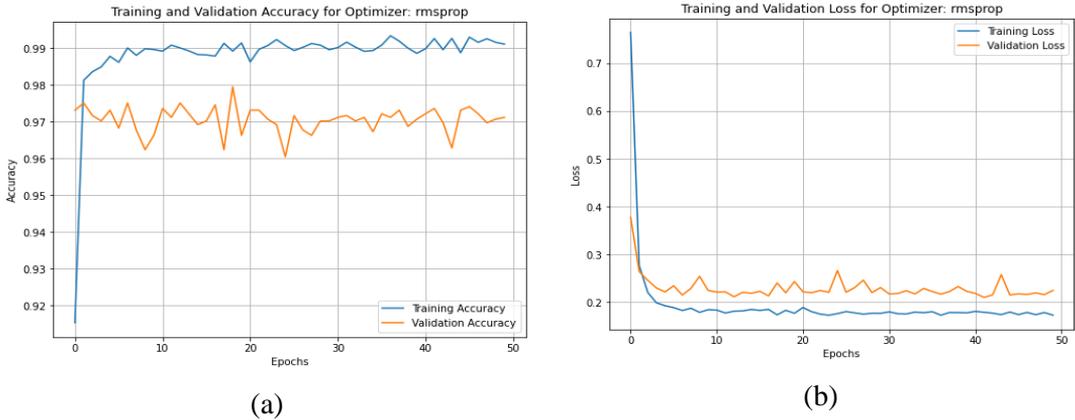


Fig 9. Feature fusion model with RMSProp optimizer

(a) Training - Validation Accuracy and (b) Training - Validation Loss.

In Fig 10, (a) shows the plot of accuracy of the model over the training and validation data, and (b) shows the plot of loss of the model over the training and validation data using the SGD optimizer. The training accuracy rapidly increases and stabilizes close to 99%, with minor fluctuations. The validation accuracy initially follows a similar pattern but shows significant drops at certain points, indicating variability in model performance across epochs. The training loss decreases sharply and stabilizes at a low value, while the validation loss shows spikes, particularly at the same points where validation accuracy drops, indicating moments of instability during training.

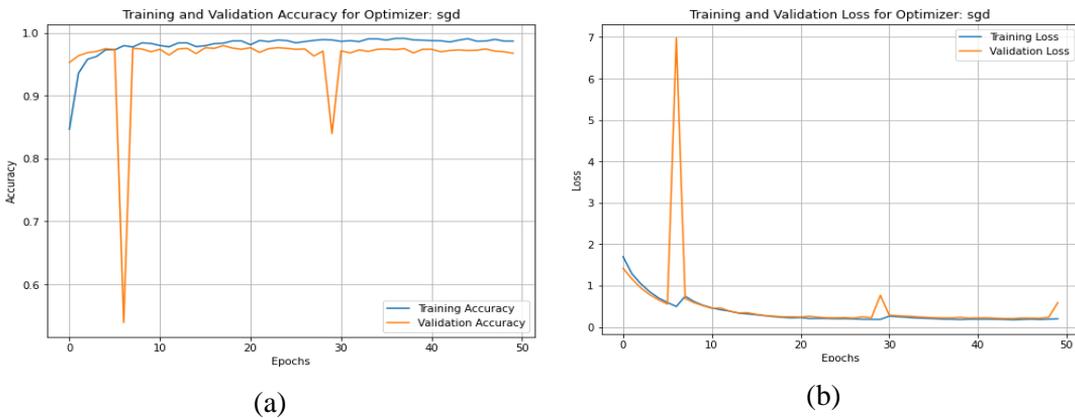


Fig 10. Feature fusion model with Sgd optimizer

(a) Training - Validation Accuracy and (b) Training - Validation Loss.

9. Conclusion

This study introduces a novel approach for classifying EEG signals to detect Mild Cognitive Impairment (MCI) by integrating traditional time-domain features with deep learning features extracted via Recurrent Neural Network (RNN). Central to this approach is the Deep Temporal Feature Integration (DTFI) method, which effectively combines static time-domain features—such as Hjorth parameters, Kurtosis, and Zero-Crossing Rate (ZCR)—with dynamic temporal features captured by the RNN. The DTFI method incorporates an attention mechanism to enhance feature weighting, ensuring that the most relevant features are prioritized during classification. This fusion significantly boosts classification accuracy, achieving 97.75% on the test set, and demonstrates the power of integrating multiple feature sets with advanced neural networks for clinical applications like early MCI detection. This research underscores the potential of DTFI and hybrid feature extraction methods in advancing EEG signal classification and improving diagnostic accuracy in neurological disorders.

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