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Research Article

Comparative Evaluation of EEG signals for Mild Cognitive Impairment using Scalograms and Spectrograms with Deep Learning Models

Saroja PATHAPATI[1]*, N. J. NALINI[2], Mahesh GADIRAJU[3]

[1]Research Scholar, Department of Computer Science and Engineering, FEAT, Annamalai University, Chidambaram, Tamilnadu-608002, India.
* **Corresponding Author Email:** pathapati.saroja@gmail.com - **ORCID:** 0000-0003-4599-9527

[2]Associate Professor, Department of Computer Science and Engineering, FEAT, Annamalai University, Chidambaram, Tamilnadu-608002, India.
Email: njncse78@gmail.com - **ORCID:** 0000-0001-8054-2501

[3]Professor, Department of Computer Science and Engineering, S.R.K.R. Engineering College, Bhimavaram, Andhra Pradesh-534204, India.
Email: mahesh.gadiraju@gmail.com - **ORCID:** 0000-0002-2577-1018

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Convolutional Recurrent Neural Networks (CRNN).

Abstract:

Electroencephalography (EEG) is a valuable tool for studying brain function and identifying neurological disorders. This study aimed to analyze EEG data using various techniques for feature extraction and classification. The data was preprocessed by applying filters and dividing it into epochs. Feature extraction techniques, including Fast Fourier Transform (FFT) in the frequency domain and Continuous Wavelet Transform (CWT) in the time-frequency domain, were applied to convert the EEG signals into scalograms and spectrograms. The primary objective was to classify individuals with Mild Cognitive Impairment (MCI) and Healthy Controls (HC) using the scalograms and spectrograms with 2D Convolutional Neural Networks (CNN) and 2D Convolutional Recurrent Neural Networks (CRNN). The classification results obtained from epochs of different durations (5 seconds and 2 seconds) were compared. The analysis revealed that the 2D CRNN model incorporating scalograms achieved the highest classification accuracy of 87.79% for 5 sec epochs and 88.25% for 2 sec epochs. This demonstrates the effectiveness of using scalograms and spectrograms in combination with deep learning models for accurately classifying individuals with MCI and HC with EEG data.

1. Introduction

Mild cognitive impairment (MCI) is a condition that is characterized by a decline in cognitive abilities, such as memory, attention, and language, that is greater than what is expected for a person's age and education level, but not severe enough to interfere significantly with daily activities. MCI is considered a transitional state between normal aging and dementia, and it is estimated that between 10% and 20% of people aged 65 or older have MCI [1-2].

Early detection of MCI is important because it provides an opportunity for early intervention and treatment, which may help delay or prevent the progression to Alzheimer's disease. There are several diagnosis methods for MCI, including cognitive testing, medical history and physical examination, and brain imaging. However, these methods can be time-consuming, expensive, and may not be sensitive enough to detect early stages of MCI.

Electroencephalography (EEG) is a non-invasive and relatively inexpensive technique for measuring the electrical activity of the brain [3]. EEG signals can provide information about the functional connectivity and activity of different brain regions, which can be used to identify changes in brain function associated with MCI. EEG signals can be collected using electrodes placed on the scalp, and the data can be processed and analyzed using various techniques to extract features that are relevant to MCI classification. In recent years, there has been growing interest in using EEG signals for the classification of MCI [4]. Several previous studies have explored different feature extraction techniques and machine learning models for Mild Cognitive Impairment (MCI) classification using EEG signals. Integrated MCI detection frameworks based on spectral-temporal analysis have been proposed, achieving accuracies ranging from 71.9% to 87.5% [5]. A multi-domain feature extraction technique on of resting-state EEG for the classification of MCI is achieved by an accuracy of 71.9% [6]. Furthermore, studies have focused on using working memory-induced intra-subject variability of resting-state EEGs, achieving an accuracy of 87.5 [7]. Other studies have focused on the classification of MCI using multi-domain features of resting-state EEG. Methods for automatic epileptic seizure detection in EEG signals using multi-domain feature extraction and nonlinear analysis, as well as hybrid multi-domain feature sets combining functional connectivity network and time-frequency features for EEG-based mental stress assessment, have been proposed [8-9].

Additionally, studies have investigated the use of EEG signals for the early detection of MCI. Methods based on EEG relative power and deep neural networks have been proposed for the detection of early-stage Alzheimer's disease, achieving accuracies of 80.0% [10].

The research gaps in previous studies:

- Studies in the past have shown inconsistent results regarding the most effective feature extraction techniques and machine learning models for MCI classification using EEG signals.
- The use of relatively small datasets in these studies raises questions about the generalizability of the models to larger datasets.
- Limited exploration of feature extraction techniques and deep learning techniques.
- Due to these limitations, there is a need for further research to determine the most effective feature extraction techniques and deep learning models for MCI classification using EEG signals.

The main aim of this study is to investigate the classification of individuals with Mild Cognitive Impairment (MCI) and Healthy Controls (HC) using EEG signals and compare the effectiveness of feature extraction techniques in the frequency domain and time-frequency domain. The study applies 2D CNN and 2D CRNN models to classify the EEG signals and evaluate their performance. This research could help to create better tools for diagnosing MCI and contribute to a deeper understanding of the condition.

2. Material and Methods

2.1 Dataset Description

The study utilized a dataset of EEG signals collected from the Isfahan MISP database, which included 61 participants aged 55. The participants were divided into two groups: 29 with Healthy Control and 32 with Mild cognitive impairment (MCI). The EEG signals were recorded during morning sessions with the participants' eyes closed, using a Galileo NT device with 19 electrodes based on the international 10-20 system (including Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2). The data was recorded using 32 channel digital EEG device with 256 Hz sampling rate and saved in EDF format [11-12].

2.2 Preprocessing Methods

Preprocessing is the process of preparing and cleaning raw data to make it suitable for analysis. In EEG signals, preprocessing is important to remove unwanted artifacts and noise that can interfere with the accuracy of the analysis [13].

Filtering

A band-pass filter is a signal processing technique used to selectively pass a specific range of frequencies while suppressing others. For preprocessing the data, a band-pass filter with a lower frequency cutoff of 0.5 Hz and an upper frequency cutoff of 45 Hz was applied. This filter helps eliminate unwanted noise and frequencies that fall outside the desired range. The selected frequency range is often utilized in EEG research to capture the patterns of brain activity associated with cognitive processing.

Epoch division

In EEG data analysis, an epoch is a specific segment of time that is isolated for examination. Dividing the EEG signal into epochs is crucial for processing the data as it allows us to identify and study particular patterns or events that could be related to different cognitive processes or states [14]. The choice of epoch length is an important consideration in EEG analysis, as it can impact the ability to identify specific patterns or events in the signal. Here, the EEG signal is divided into epochs of 5 seconds and 2 seconds using the make_fixed_length_epochs function from the MNE library with 1 sec overlap. In this study, 5-second epochs were used as they capture relevant neural activity while reducing computational demands, whereas 2-second epochs require more resources (the difference in accuracy is very low just 0.1 or less). The sample EEG signal for 1 minute epoch division is shown in Figure 1.

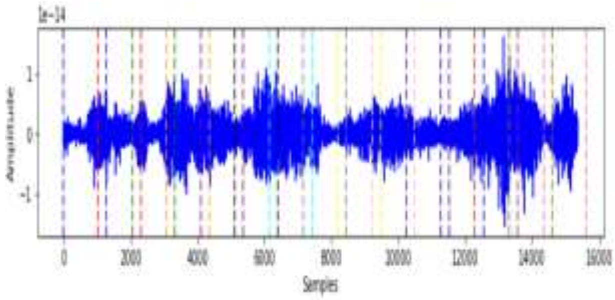


Figure 1. *Sample EEG Signal shown for 1 minute.*

2.3 Feature extraction techniques

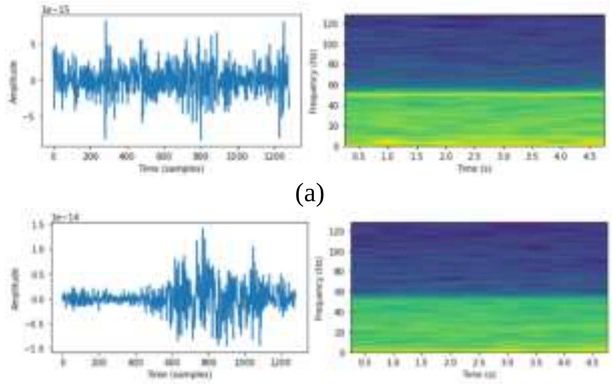
Feature extraction techniques are used to identify important patterns and characteristics from raw data. In EEG signals, feature extraction is important because it helps reduce the dimensionality of the data, improves classification accuracy, and provides insights into underlying cognitive processes. Time-domain, frequency-domain, and time-frequency features are commonly used in EEG signal analysis [15].

Short Time Fourier Transform (STFT)

STFT is a method of analyzing signals in the frequency domain. Unlike the standard Fourier Transform (FT), which provides a frequency representation of the entire signal, STFT breaks down a signal into its frequency content over small, overlapping time segments. This allows for the examination of frequency changes over time.

In EEG signals, STFT can be used to analyze the time-varying frequency content of the signal, providing information about changes in brain activity over time [16]. It is particularly useful for examining changes in frequency content during specific events or tasks, such as during a seizure or during a cognitive task. STFT is often used to generate spectrograms, which provide a visual representation of frequency content over time.

The plt.specgram() function takes an EEG epoch and returns a 2D array representing the spectrogram, where the x-axis represents time, and the y-axis represents frequency. The function applies a Short-Time Fourier Transform (STFT) to the EEG epoch, which involves dividing the epoch into shorter segments, applying the FFT to each segment, and stacking the results to create a 2D matrix of frequencies and their corresponding magnitudes for each time segment. The resulting matrix is then plotted as a spectrogram using the plt.imshow() function. Finally, the spectrogram is saved as a PNG image using the plt.savefig() function. The Spectrogram images is shown in Figure 2.



(a)

(b)

Figure 2. *Spectrogram Images of EEG Signals for a). Healthy Controls (HC) and b). Mild Cognitive Impairment (MCI) Patients.*

Continuous Wavelet Transform (CWT)

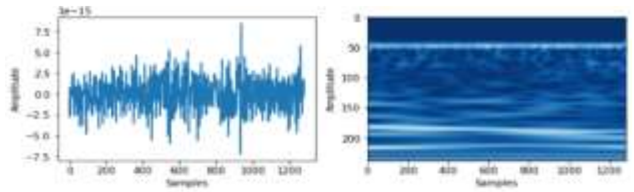
The Continuous Wavelet Transform (CWT) is a mathematical tool that allows for analyzing signals in both the time and frequency domains simultaneously. It is important in EEG signal processing because it can identify subtle changes in frequency content over time [17]. The cwt function from ssqueezepy package is used to calculate the continuous wavelet transform of each EEG epoch signal in the control_epochs_array. The Morlet wavelet is used as the mother wavelet for transformation. The resulting wavelet coefficients Wx and associated scales are returned. Then, the absolute values of Wx are calculated and an image is generated using plt.imshow function. This image is a scalogram representation of the signal where the x-axis represents time, the y-axis represents frequency, and the color intensity represents the magnitude of the wavelet coefficients. The scalogram images for HC and MCI patients is shown in Figure 3.

2.4 Deep Learning Techniques

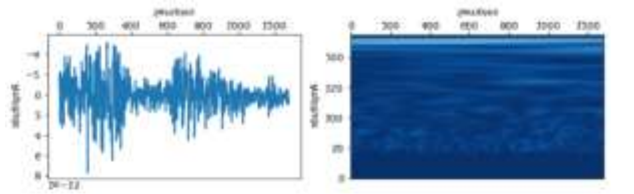
Deep learning techniques refer to a subset of machine learning methods that helps to perform complex tasks such as image recognition, natural language processing, and predictive analytics. These techniques are important for EEG signals because they can help extract meaningful features from the raw data and improve the accuracy of classification and prediction models, which are useful for diagnosing neurological disorders and understanding brain function.

2D CNN (Convolutional Neural Network)

2D CNN is a type of neural network architecture that can analyze two-dimensional data, such as images. It is particularly useful for EEG signal analysis when the data is represented in the form of



(a)



(b)

Figure 3. *Scalogram Images of EEG Signals for a). Healthy Controls (HC) and b). Mild Cognitive Impairment (MCI) Patients.*

spectrograms or scalograms, as it can learn to identify patterns and features within the images, making it a powerful tool for EEG signal classification [18-20]. The architecture diagram of CNN is shown in Figure 4.

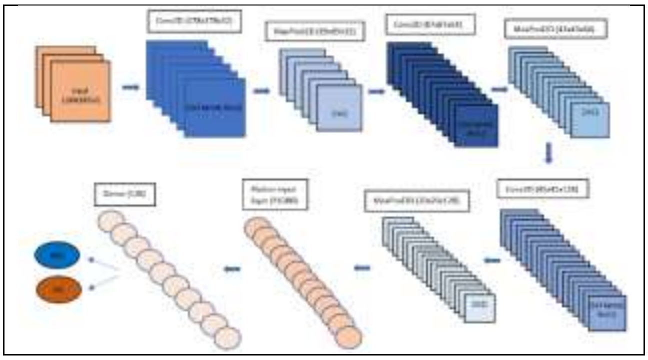


Figure 4. *Architecture of 2D Convolutional Neural Network*

The architecture for the 2D CNN that we use in our work includes-

- Input layer: The input layer takes in an image with dimensions of 180x180x3, where 3 represents the number of channels (red, green, and blue).
- Convolutional layer 1: The first convolutional layer applies 32 filters of size 3x3 to the input image. The activation function used is ReLU, which introduces non-linearity to the model.
- Max pooling layer 1: The max pooling layer reduces the size of the feature map by taking the maximum value of a 2x2 pooling window. This helps in reducing the computational complexity of the model.
- Convolutional layer 2: The second convolutional layer applies 64 filters of size 3x3 to the output of the first max pooling layer. Again, the activation function used is ReLU.
- Max pooling layer 2: The second max pooling layer further reduces the size of the feature map by taking the maximum value of a 2x2 pooling window.
- Convolutional layer 3: The third convolutional layer applies 128 filters of size 3x3 to the output of the second max pooling layer. The activation function used is ReLU.
- Max pooling layer 3: The third max pooling layer further reduces the size of the feature map by taking the maximum value of a 2x2 pooling window.
- Flatten layer: The flatten layer converts the output of the third max pooling layer into a 1D vector that can be fed into a fully connected layer.
- Fully connected layer 1: The first fully connected layer has 128 neurons and uses ReLU activation function.
- Output layer: The output layer has 2 neurons (for MCI and HC) and uses softmax activation function to output probabilities of the input image belonging to each class.

2D CRNN (Convolutional- Recurrent Neural Network)

A 2D CRNN, or Convolutional Recurrent Neural Network, is a type of deep learning model that combines the convolutional layers of a CNN with the recurrent layers of an RNN to process 2D sequential data, such as images or videos, with temporal information. This allows the model to capture both spatial and temporal patterns in the data, making it useful for tasks such as image classification, video recognition, and speech recognition. The architecture diagram of 2DCRNN is shown in Figure 5.

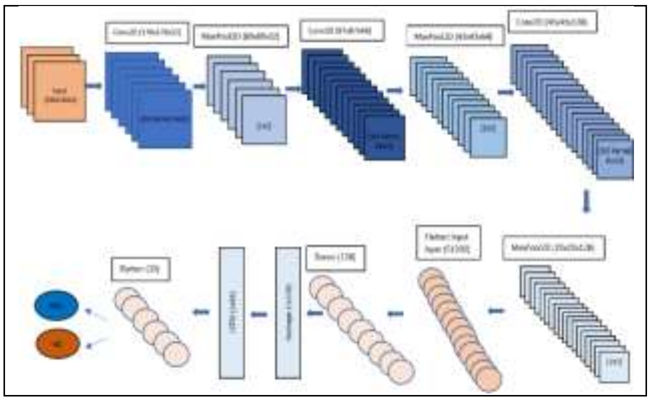


Figure 5. *Architecture diagram of 2D Convolutional Recurrent Neural Network*

- The input layer receives an image of shape (img_width, img_height, 3), where img_width and img_height represent the dimensions of the input image, and 3 represents the RGB color channels of the image.

- The first convolutional layer Conv2D applies 32 filters with a 3x3 kernel and ReLU activation. This layer learns 32 feature maps of size (img_width - 2, img_height - 2).
- The first max pooling layer MaxPooling2D performs 2x2 pooling operation with a stride of 2, reducing the spatial dimensions by half. This results in feature maps of size (img_width // 2 - 1, img_height // 2 - 1).
- The second convolutional layer Conv2D applies 64 filters with a 3x3 kernel and ReLU activation. This layer learns 64 feature maps of size (img_width // 2 - 2, img_height // 2 - 2).
- The second max pooling layer MaxPooling2D performs 2x2 pooling operation with a stride of 2, reducing the spatial dimensions by half. This results in feature maps of size (img_width // 4 - 1, img_height // 4 - 1).
- The third convolutional layer Conv2D applies 128 filters with a 3x3 kernel and ReLU activation. This layer learns 128 feature maps of size (img_width // 4 - 2, img_height // 4 - 2).
- The Flatten layer converts the 3D tensor output of the previous layer into a 1D tensor for use by the fully connected layers.
- The Reshape layer converts the 1D tensor into a 2D tensor of shape (1, 128). This is necessary to feed the output of the convolutional layers to the recurrent layers.
- The first recurrent layer LSTM applies 64 units with a tanh activation function and returns sequences. This layer processes the input sequence of feature vectors generated by the convolutional layers, and outputs a sequence of hidden states.
- The Flatten layer converts the output of the recurrent layer into a 2D tensor.
- The fully connected Dense layer applies 128 units with a ReLU activation function. This layer learns a representation of the input sequence for classification.
- The output Dense layer applies num_classes units with a softmax activation function. This layer outputs a probability distribution over the num_classes classes.

3. Results and Discussions

Experimental results were conducted to classify EEG signals for both MCI and HC subjects, utilizing epochs of 5 seconds and 2 seconds. The 5-second epochs, with a 1-second overlap, consisted of N = 1280 data points (corresponding to a sampling frequency of 256 Hz), totaling 28,402 input EEG data points. Each epoch was defined consecutively, with the first epoch spanning from 1 to 5 seconds, the second epoch from 4 to 9 seconds, and so on. The dataset included data from 14,757 subjects with Mild Cognitive Impairment (MCI) and 13,645 Healthy Control (HC) subjects. Similarly, the 2-second epochs, also with a 1-second overlap, comprised N = 512 samples (2 x 256), resulting in a total of 56,860 input data points. The dataset for these epochs consisted of data from 29,540 MCI subjects and 27,320 HC subjects.

Performance metrics are important because they allow us to objectively evaluate the performance of a model and compare it to other models or benchmarks. Accuracy is a performance metric that measures the proportion of correct predictions made by a model over the total number of predictions made. In other words, accuracy tells us how often a model is correct when it makes a prediction.

$$\mathrm{A} = \frac{\mathrm{tp} + \mathrm{tn}}{\mathrm{tp} + \mathrm{fp} + \mathrm{tn} + \mathrm{fn}} \qquad (1)$$

where tp is true positive, tn is true negative, fp is false positive and fn is false negative.

The spectrogram images obtained using Short Time Fourier Transform from EEG signals are divided into train and test sets of 75% and 25% respectively. These train and test sets are given as input to 2D CNN [20]. The model is trained using the ImageDataGenerator class of Keras, which allows the input images to be fed to the model. The train_datagen and test_datagen objects are created with the rescale parameter set to 1/255, which scales the pixel values of the input images to the range [0, 1].

The train_generator and test_generator is created using the flow_from_directory method, which reads images from the directories 'spectrograms/train' and 'spectrograms/test', respectively. These directories have the structure of subdirectories, where each subdirectory corresponds to one class, and contains images of that class. The class_mode parameter is set to 'categorical', indicating that the labels are represented as one-hot encoded vectors. The Classification of EEG signals using spectrogram and 2D CNN is shown in Figure 6.

2D CRNN is used to classify spectrogram images into two categories: MCI and HC. The dataset was divided into 75% training set and 25% testing set. The model was trained on the training set using the fit method. Afterwards, its performance is evaluated on the test set using the evaluate method. For 5-second epochs with 1 second overlap an accuracy of 84.95% is achieved, while for 2-second epochs with 1 second overlap, the accuracy achieved is 84.06%. The classification of EEG signals using spectrogram and 2D CRNN is shown in Figure 7.

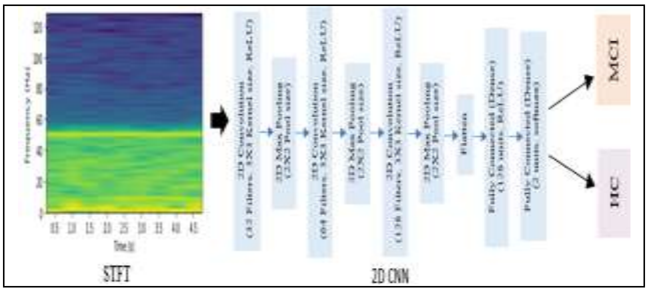


Figure 6. *Classification of EEG signals using Spectrogram and 2D CNN*

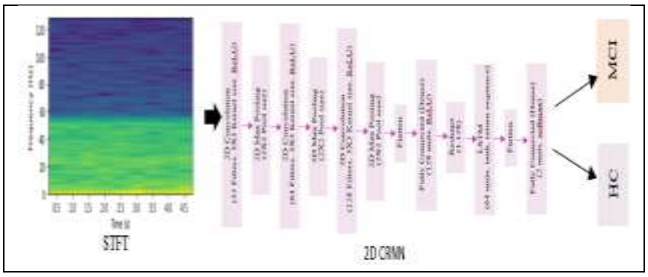


Figure 7. *Classification of EEG signals using Spectrogram Image and 2D CRNN*

Continuous Wavelet Transform with 2D CNN

The scalogram images obtained by CWT are divided into training and testing sets using the train_test_split function, with a split ratio of 75:25. The model is then trained using the fit method, where the training data generator and the number of training epochs are specified. The performance of the model is assessed on the testing data after each epoch using the validation_data parameter. Finally, the model is evaluated on the testing data using the evaluate method to obtain its accuracy. The accuracy obtained for 5-second epochs is 86.46%, while for 2-second epochs, it is 86.98%. The classification of EEG signals using scalograms and 2DCNN is shown in Figure 8 and Categorizing HC and MCI Classes using CWT-based scalogram images as input for 2D CRNN is shown in figure 9.

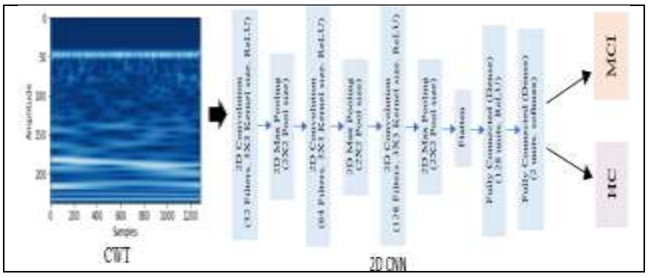


Figure 8. *Utilizing CWT-based Scalogram Images as Input for 2D CNN to Classify HC and MCI Classes*

The model is set up with specific settings, including the loss function, optimizer, and metric used to measure its performance. It is trained on the training data for a certain number of cycles, and after each cycle, its performance is checked on the test data. Finally, the model is assessed on the test data to see how well it performs. The accuracy achieved when using the CRNN model with 5-second epochs is 87.79%, while for 2-second epochs, it reaches 88.45%. The classification accuracies for spectrogram and scalograms are shown in Table 1 and Figure 10. The CNN is an important method and used for different application in literature [21-24].

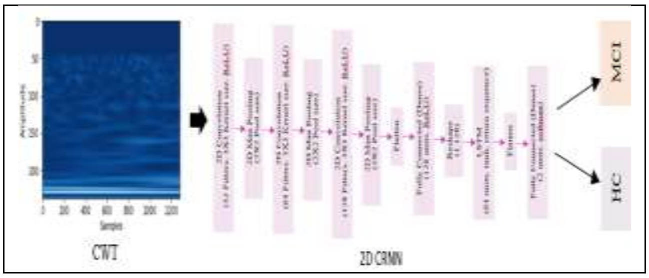


Figure 9. *Categorizing HC and MCI Classes using CWT-based Scalogram Images as Input for 2D CRNN.*

Table 1. *Comparison of Accuracy for Different Feature Extraction Techniques and Deep Learning Models.*

Deep Learning Techniques	Feature Extraction Techniques	Accuracy in %	
		For 5 secs	For 2 secs
2D CNN	Spectrograms	82.06	82.57
	Scalograms	86.46	86.98
2D CRNN	Spectrograms	84.95	84.06
	Scalograms	87.79	88.25

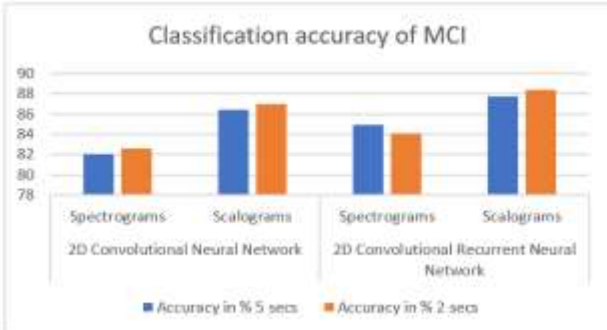


Figure 10. *Classification Accuracy of MCI for 2 secs and 5 secs*

4. Conclusions

This study recommends using 5-second epochs with a 1-second overlap when analyzing EEG data to distinguish individuals with Mild Cognitive Impairment (MCI) from Healthy Controls. While 2-second epochs with overlap showed slightly higher accuracy, the study aimed to strike a balance between accuracy and resource efficiency. By utilizing 5-second epochs, we can maintain a satisfactory level of accuracy while optimizing computational resources. The comparison between epoch divisions with and without overlap confirmed the superiority of epochs with overlap, as they capture temporal dependencies within the EEG data, resulting in improved classification performance. Future research should focus on optimizing the performance of 5-second epochs through advanced feature extraction techniques or model enhancements to bridge the accuracy gap observed with shorter epochs.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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