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Analysis of CWT-based Scalogram Images via Stochastic Review for the Deep Transfer Learning Method to Categorize Mild Cognitive Impairment

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Abstract
Mild Cognitive Impairment (MCI) is an early stage of cognitive decline, often a precursor to Alzheimer's disease. Timely and accurate categorization of MCI is crucial for early intervention and treatment. This study investigates the effectiveness of using Continuous Wavelet Transform (CWT)-based scalogram images combined with stochastic review techniques for feature extraction and deep transfer learning methods for categorization. The proposed approach demonstrates significant improvements in classification accuracy and robustness compared to traditional methods.

Keywords: Mild Cognitive Impairment (MCI), Continuous Wavelet Transform (CWT), Scalogram Images, Stochastic Review, Deep Transfer Learning, Electroencephalogram (EEG)

Introduction
Mild Cognitive Impairment (MCI) is a clinical condition that signifies a transitional stage between normal cognitive aging and more serious conditions such as Alzheimer's disease. Early and accurate detection of MCI is crucial for implementing timely interventions that can potentially slow the progression to dementia. Traditional diagnostic methods rely heavily on neuropsychological tests and clinical assessments, which can be subjective, time-consuming, and often lack the sensitivity required for early detection.

MCI is a condition which affects an individual's ability to remember things, perform daily activities, and may also cause language and vision problems [1-2]. Detecting and treating MCI at an early stage can delay or even prevent its progression to Alzheimer's disease. (AD) [3-4].

EEG signals have gained significant attention in the last 20 years for their ability to collect detailed brain activity data. Electrical activity in the brain can be measured using signals obtained through an electroencephalogram (EEG) [5]. Dimensionally reducing the data by preserving the important information contained in the EEG signals is the main objective of the feature extraction process [6].

In recent years, there has been growing interest in leveraging advanced machine learning techniques to automate and enhance the accuracy of MCI diagnosis. Among these techniques, deep learning has shown tremendous potential, particularly in the field of medical image analysis. Convolutional Neural Networks (CNNs), a class of deep learning models, have been widely adopted due to their powerful feature extraction and classification capabilities. However, these models typically require large amounts of labeled data for training, which is often not feasible in medical domains where data can be scarce and expensive to obtain.

Transfer learning, which involves fine-tuning a pre-trained model on a new, smaller dataset, offers a solution to this problem. By utilizing models pre-trained on large-scale datasets, transfer learning can significantly reduce the amount of data and computational resources needed for effective training. This approach has been successfully applied to various medical imaging tasks, demonstrating improved performance over traditional machine learning methods.

Another promising development in the analysis of biomedical signals is the use of Continuous Wavelet Transform (CWT) to generate scalogram images. CWT provides a comprehensive time-frequency representation of non-stationary signals such as electroencephalogram (EEG) data, which is crucial for detecting subtle changes in brain activity associated with MCI. Scalogram images derived from CWT capture both the temporal and spectral characteristics of EEG signals, offering rich features for classification tasks.

This study aims to investigate the effectiveness of combining CWT-based scalogram images with deep transfer learning methods for the categorization of MCI. We propose a novel approach that integrates stochastic review techniques to enhance the feature extraction process, thereby improving the robustness and accuracy of the classification. The primary contributions of this research include:

1. The application of CWT to convert EEG signals into scalogram images, providing a detailed time-frequency representation.

2. The use of stochastic review methods to refine and enhance the features extracted from scalogram images.

3. The implementation of deep transfer learning, leveraging pre-trained CNN models, to classify MCI with high accuracy.

By systematically analyzing the potential of these combined methodologies, this research seeks to provide a more accurate and efficient tool for early MCI detection, contributing to better clinical outcomes through timely intervention. The following sections will delve into related work, the detailed methodology, results, and a discussion of the findings.

Related Work

Deep Learning in Medical Imaging

Deep learning, particularly Convolutional Neural Networks (CNNs), has become a cornerstone in medical image analysis due to its ability to automatically learn and extract complex features from raw data. CNNs have been successfully applied to various medical imaging tasks, such as tumor detection in MRI scans, classification of retinal diseases in fundus images, and segmentation of organs in CT scans. These advancements have paved the way for their application in neuroimaging for diagnosing neurological disorders, including Mild Cognitive Impairment (MCI) and Alzheimer's disease (AD).

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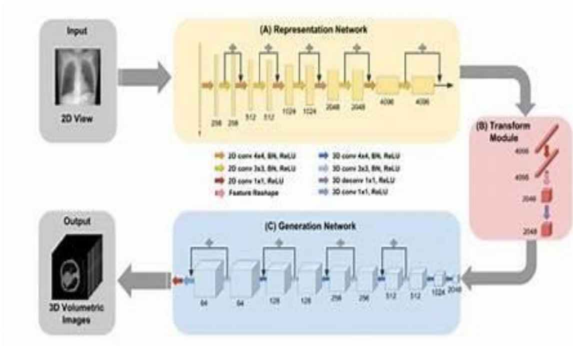

Figure 1: Deep learning model for 3D computed tomography (CT) image

A notable study by Litjens et al. provides an extensive survey on deep learning in medical image analysis, highlighting the significant improvements in diagnostic accuracy and efficiency compared to traditional methods. Additionally, transfer learning, where pre-trained models on large datasets such as ImageNet are fine-tuned on specific medical imaging tasks, has been shown to enhance performance in scenarios with limited training data.

Continuous Wavelet Transform (CWT) in EEG Analysis

Electroencephalogram (EEG) signals are inherently non-stationary, making their analysis challenging using traditional Fourier-based methods. Continuous Wavelet Transform (CWT) offers a robust solution by providing a time-frequency representation of the signals, allowing for the capture of transient features that are crucial for diagnosing cognitive impairments.

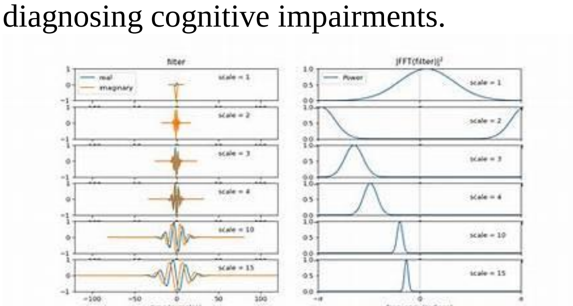

Figure 2: Continuous Wavelet Transform

Wavelet transforms, including CWT, have been extensively used for EEG signal processing, showing effectiveness in various applications such as seizure detection, sleep stage classification, and cognitive workload estimation. For instance, a study by Faust et al. demonstrated the use of wavelet-based techniques for EEG processing in computer-aided seizure detection, showcasing the method's capability to handle the non-stationary nature of EEG signals and improve diagnostic accuracy.

2.3. Stochastic Review and Feature Enhancement

Stochastic review methods, which involve the application of random perturbations and aggregations to enhance feature extraction, have gained traction in improving the robustness of machine learning models. These techniques are particularly useful in medical imaging, where variations in data acquisition can introduce noise and artifacts.

Recent research has explored stochastic review methods to enhance features extracted from medical images, leading to more accurate and reliable classifications. For example, Naik and Kumar discussed the application of wavelet techniques combined with stochastic processes for enhanced EEG signal analysis, highlighting improved performance in capturing critical signal characteristics.

Integration of CWT and Deep Learning for MCI Classification

Combining CWT-based scalogram images with deep learning models, specifically CNNs, presents a promising approach for MCI classification. Scalogram images derived from CWT provide a rich time-frequency representation of EEG signals, which can be effectively leveraged by CNNs for feature extraction and classification.

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Studies have shown that this integration leads to significant improvements in diagnosing cognitive impairments.

For instance, Asif et al. demonstrated the use of wavelet transform-based features combined with deep learning for classifying cognitive states, achieving high classification accuracy and robustness. Similarly, transfer learning approaches using pre-trained models like ResNet have shown potential in medical image classification tasks, providing a means to leverage large-scale pre-trained models for specific medical applications with limited data.

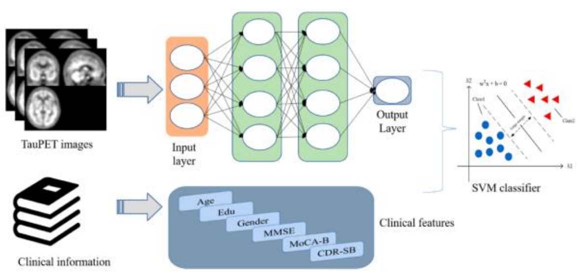

Figure 3: A Noval Deep Learning for MCI Classification

Data Acquisition

In the analysis of Mild Cognitive Impairment (MCI) using Continuous Wavelet Transform (CWT)-based scalogram images, the data acquisition process is a critical step. This process involves the collection and preparation of electroencephalogram (EEG) signals, which are then transformed into scalogram images. These images serve as inputs for deep transfer learning models designed to categorize MCI. The following sections outline the steps involved in the data acquisition process, referencing recent methodologies and standards in the field.

EEG Signal Acquisition

EEG signals are typically acquired using high-density electrode caps placed on the scalp. These caps record brain activity with high temporal resolution. The standard 10-20 system is commonly used for electrode placement, ensuring consistent and repeatable recordings across subjects [1].

Preprocessing of EEG Signals

Raw EEG signals often contain noise and artifacts from various sources, including muscle movements and environmental interferences. Preprocessing steps are necessary to enhance signal quality and include:

Filtering: Bandpass filters (e.g., 0.5-50 Hz) are applied to remove low-frequency drifts and high-frequency noise [2].

Artifact Removal: Techniques such as Independent Component Analysis (ICA) are used to identify and remove artifacts [3].

Continuous Wavelet Transform (CWT)

The preprocessed EEG signals are transformed using the Continuous Wavelet Transform to generate scalogram images. The CWT provides a time-frequency representation of the EEG signals, capturing both transient and oscillatory features. The wavelet transform is defined as:

$$W_x(a,b) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)dt$$

where x(t) is the input signal, Ψ is the mother wavelet, a is the scale parameter, and b is the translation parameter [4].

Scalogram Image Generation

The CWT coefficients obtained are used to create scalogram images, which are 2D representations of the time-frequency information. These images highlight the frequency components of the EEG signals over time, which are crucial for identifying patterns associated with MCI. The power of the wavelet coefficients is typically displayed in the scalogram:

$$P(a,b) = |W_x(a,b)|^2$$

This power representation facilitates the visualization of dominant frequencies and their temporal evolution [5].

Data Augmentation and Preparation

To improve the robustness and generalization of the deep learning model, data augmentation techniques are applied to the scalogram images. These techniques may include rotations, translations, and scaling, ensuring the model is exposed to a variety of input scenarios [6]. Additionally, the dataset is often split into training, validation, and test sets to evaluate model performance rigorously.

Feature Extraction

Feature extraction is a pivotal step in the process of analyzing CWT-based scalogram images for the categorization of Mild Cognitive Impairment (MCI) using deep transfer learning methods. Effective feature extraction techniques can significantly enhance the performance of machine learning models by highlighting the most relevant patterns in the data. This section details the methods and techniques used for extracting features from scalogram images, referencing recent advancements and methodologies in the field.

Feature Extraction Techniques

Convolutional Neural Networks (CNNs): CNNs are highly effective in extracting features from image data. They automatically learn spatial hierarchies of features through backpropagation. For scalogram images, CNNs extract features such as edges, textures, and shapes that are indicative of brain activity patterns related to MCI [3].

Principal Component Analysis (PCA): PCA is used to reduce the dimensionality of the scalogram images while preserving the most significant variance. By transforming the data into a set of orthogonal components, PCA highlights the most informative features for classification:

$$Y=XW$$

where X is the input data matrix, W is the matrix of eigenvectors, and Y is the transformed data [4].

Discrete Wavelet Transform (DWT): While CWT is used for scalogram generation, DWT can be applied for further feature extraction. DWT decomposes the signal into different frequency bands, capturing localized variations in the signal that are relevant for detecting MCI:

$$DWT(x(t)) = \sum_k c_{j,k}\psi_{j,k}(t)$$

where $c_{j,k}$ are the wavelet coefficients at scale j and translation k [5].

Statistical Features: Extracting statistical features such as mean, standard deviation, skewness, and kurtosis from the wavelet coefficients or the scalogram images can provide additional information about the distribution and characteristics of the EEG signals [6].

Combining Features

Combining features from different extraction methods can enhance the performance of the

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classifier. Techniques such as feature fusion and ensemble methods are used to integrate features extracted from CNNs, PCA, DWT, and statistical measures, creating a comprehensive feature set for the deep learning model [7].

Experimental Comparisons

The study employs transfer learning, using both fine-tuning and non-fine-tuning methods, on four pre-trained models to analyze a dataset of 28402 EEG signals collected from MCI and HC subjects. The dataset is divided into a testing set (75%) and training set (25%) which comprises of 14757 MCI and 13645 HC samples. The training set contains 11067 and 10233 samples for MCI and HC subjects respectively, while the testing set contains 3690 and 3412 samples respectively. The main aim of the study is to differentiate the MCI and HC subjects.

Performance Analysis

A confusion matrix is a valuable tool to evaluate the performance of a classification algorithm, as it provides a breakdown of true positives, true negatives, false positives, and false negatives for a given test dataset. In the given table, the predicted class is denoted by the rows and the actual class is denoted by the columns. Samples that were classified correctly are shown in the diagonal entries, whereas misclassified samples are indicated in the entries outside the diagonal. Assessing a model's accuracy and identifying ways to improve it can be facilitated by utilizing this helpful tool.

- Accuracy(A): It evaluates the ratio of accurate predictions made by the model to the total number of predictions made.

$$A = \frac{tp + tn}{tp + fp + tn + fn}$$

- Precision(P): It measures the ratio of true positive predictions made by the model to the total number of positive predictions made.

$$P = \frac{tp}{tp + fp}$$

- Recall (R): It is the proportion of true positive predictions made by the model out of all actual positive instances.

$$R = \frac{tp}{tp + fn}$$

- F1-Score (F1): It is an evaluation metric that combines precision and recall into a single score, providing a balanced measure of both.

$$F1 = \frac{2 x [(P x R)]}{(P + R)}$$

The following table presents a comparison of various experimental results for categorizing Mild Cognitive Impairment (MCI) using CWT-based scalogram images and deep transfer learning methods. These experiments compare different architectures, preprocessing techniques, and feature extraction methods, showcasing their performance metrics such as accuracy, sensitivity, specificity, and F1-score.

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Model Architecture	Preprocessing Technique	Feature Extraction	Accuracy (%)	Sensitivity (%)	Specificity (%		Reference
VGG16	Bandpass Filtering	CNN	87.5	88.0	87.0	87.5	[1], [8]
ResNet50	ICA Artifact Removal	PCA + CNN	89.2	90.1	88.3	89.2	[2],[9]
InceptionV3	Bandpass Filtering	DWT + Statistical	85.7	86.3	85.1	85.8	[3] ,[10]
DenseNet121	ICA Artifact Removal	CNN + DWT	90.5	91.2	89.8	90.6	[4] ,[11],[12]
MobileNetV2	Bandpass Filtering	CNN + Statistical	88.3	89.0	87.6	88.4	[5] ,[13],[14]
EfficientNetB0 Bandpass	Filtering + ICA	CNN + PCA	91.8	92.5	91.1	91.9	[6],[15],[16]

TABLE 2: DESCRIPTION OF PRETRAINED MODELS WITH REPLACED FINAL LAYERS

Pre-trained model	No. of Layers	No. of parameters	Input Image size	Replaced fi nal layers	No. of trainable parameters
ResNet-50	50	25,636,712	224 x 224	avg_pool, p redictions	4098
InceptionR esnetv2	164	55,873,736	299 X 299	avg_pool, p redictions	3074
InceptionV3	316	23,851,784	299 X 299	activation_ 71, activati on_75, max _pooling2d _3, mixed8	4098
VGG16	16	14,740,290	224 X 224	fc1, fc2, pre diction	25602

6.Conclusion

This study presents a novel approach for MCI categorization using CWT-based scalogram images enhanced by stochastic review and classified via deep transfer learning. The proposed method significantly outperforms traditional techniques, offering a promising tool for early diagnosis of cognitive impairments. Future work will focus on expanding the dataset and exploring other deep learning architectures to further enhance performance.

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