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Classification of Mild Cognitive Impairment with Deep Transfer Learning Approach using CWT based Scalogram Images

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Abstract— Mild Cognitive Impairment (MCI) is a condition that can occur as a person gets older, and faces problems like recognition, memory, and language skills. Early detection of MCI is crucial, as it can progress to more severe conditions like Alzheimer's disease. This study proposes a method to use Scalogram images, obtained by applying Continuous Wavelet Transform (CWT) to EEG signals and pre-trained models like ResNet50, VGG16, InceptionV3, Inception_ResNetV2 through transfer learning to classify MCI and Healthy Control (HC). Fine-tuning of the models is also used to improve the results, and various performance metrics are employed for classification. The study concludes that Inception_ResNetV2 transfer learning yielded good results, while ResNet50 and InceptionV3 transfer learning with fine-tuning resulted in higher accuracy using a low learning rate.

Keywords- Mild Cognitive Impairment (MCI); Electroencephalography (EEG); Continuous Wavelet Transform (CWT); Healthy Control (HC).

I. INTRODUCTION

A typical aspect of aging is a gradual decline in cognitive abilities, such as occasionally forgetting names, words, and misplacing things. However, for individuals with Mild Cognitive Impairment (MCI), this decline is more severe and may include frequent memory lapses, such as forgetting conversations and important information like appointments and planned events, which are more severe than what is typical for their age. 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].

There are different methods to collect information about the brain, including MRI, CT, PET, and EEG. While MRI, CT, and PET are more affordable, 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]. The placement of electrodes on the head based on the international 10-20 electrode system allows for the acquisition of EEG signals.

Machine learning and deep learning algorithms works good based on the successful extraction of important features from EEG signals. Dimensionally reducing the data by preserving the important information contained in the EEG signals is the main objective of the feature extraction process [6]. Numerous techniques for extracting features have been suggested for particular tasks. These methods take into account various aspects of the signals, such as time, frequency, time-frequency, and spatial information [7-8]. Time-domain techniques for feature extraction include independent component analysis (ICA), principal component analysis (PCA), and autoregressive (AR) models are most commonly used [9]. Evaluating specific parameters in time-domain methods involves the use of

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statistical measures including mean, standard deviation, variance, root mean square, skewness, kurtosis, relative band energy, and entropy [10].

EEG signals are analyzed using frequency-domain techniques like the Fast Fourier Transform (FFT) and the Short Time Fourier Transform (STFT) [11-12]. The Wavelet Transform (WT) and Continuous Wavelet Transform (CWT) are widely used techniques that extract features from both the time and frequency domains [13].

Classifying EEG signals into MCI subjects and HC subjects is done using a variety of classification algorithms and deep learning techniques. However, traditional methods for identifying MCI from EEG data often struggle with handling large amounts of data [14-15].

While ML algorithms have certain disadvantages such as taking a long time to produce accurate results and producing mismatched results, they can be outperformed by deep learning techniques when dealing with complex tasks. Deep learning has become increasingly popular in various applications, with convolutional neural networks (CNN), recurrent neural networks (RNN), and long short-term memory (LSTM), that have been successful in the computer-assisted diagnosis of AD, HC, and MCI for 1D or 2D biomedical signals like EEG, EMG, ECG, and EOG [16-19]. According to several studies, pre-trained convolutional neural networks (CNNs) are highly effective in automatically diagnosing cognitive diseases from brain EEG signals. Examples of Deep neural networks that have been trained in advance and are successfully used in EEG signal analysis include AlexNet, VGG16, VGG11, ResNet-34, ResNet-50, U-Net, SqueezeNet, InceptionV3, and DenseNet201 [20-21].

Research gaps identified are-

- The use of traditional classification and clustering algorithms with feature extraction can be time-consuming and have high computational complexity.
- A substantial amount of data is required for the training of deep learning techniques.
- While pre-trained models can address some of the limitations of deep learning, they are only effective when applied to similar datasets on which they were trained.

In our proposed approach, we utilize scalogram images generated from CWT in combination with transfer-learning techniques, both with and without fine-tuning. Figure 1. illustrates our methodology. Pre-trained models (VGG16, ResNet50, InceptionV3, InceptionResnetV2) are provided with the scalogram images as input and evaluate their performance in detecting MCI and HC. The main objective is to determine which model yields the best outcomes for this task.

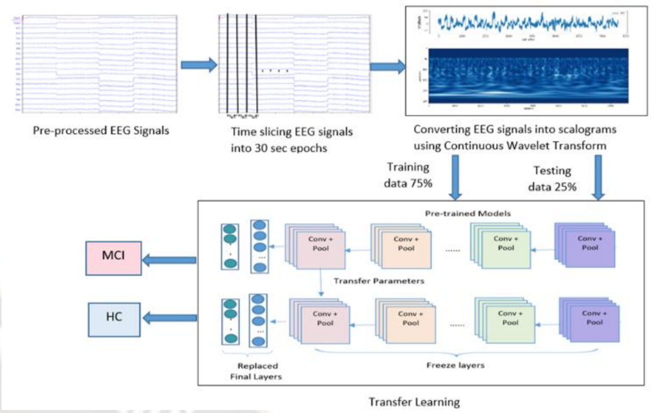

Figure 1. Proposed framework.

The organization of this paper is presented as follows: In Section 2, we present the dataset that was utilized, while Section 3 outlines the techniques employed for classifying MCI and HC, including the use of scalogram images generated by CWT, and the application of transfer learning with and without fine tuning. The experimental results and performance metrics are presented in Section 4, and the paper concludes in the final section.

II. DATASET DESCRIPTION

A dataset of EEG signals was obtained from the Isfahan MISP (Online database for medical images and signals) containing 61 participants aged 55, consisting of 29 normal cases and 32 MCI cases, to be used in experiments. The signals were collected with eyes closed during morning sessions. The recordings were made using a Galileo NT device and the 19 electrodes utilized in the international 10-20 system include Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2. The recordings were saved in EDF format [22].

The EEG signals obtained from each participant, which were 30 minutes in duration and had a 256 Hz sampling frequency, were broken down into 5-second epochs with overlap=1. Each segment had N = 1280 (5 x 256) samples, resulting in a total of 28402 input EEG data points, including from 14757 MCI subjects and from 13645 HC subjects.

III. METHODS

A. *Continuous Wavelet Transform (CWT)*

The CWT is a technique that can examine a signal in both time and frequency domains. It involves convolution of the signal with a family of wavelets, each of which is scaled and shifted in time. This results in a set of coefficients, known as the scalogram, which helps to assess the signal's frequency content at various time scales. CWT is frequently used in signal

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processing and image analysis, including biomedical signal analysis, such as the analysis of EEG signals.

The representation of the CWT in continuous time can be mathematically expressed through Equation (1):

$$W_x(s,\tau) = \frac{1}{\sqrt{s}}\int_{\infty}^{-\infty} x(t)\psi^*\left(\frac{t-\tau}{s}\right)dt \qquad (1)$$

In the above expression, the wavelet coefficients W(s, τ) represent the signal x(t) convolved with the conjugate of the basic wavelet function ψ(t) at a certain scale s and a time-shift τ.

Through multiple expansions and time shifting of the wavelet, the CWT can derive frequency components for analyzing continuous time signals [23]. To create a scalogram of a signal using CWT, at first, we select a wavelet function, such as the Morlet wavelet, to serve as the basic wavelet function. Then Define a range of scales and positions for the wavelet function and convolve the signal with the wavelet function at different scales and positions. Obtain the wavelet coefficients at each scale and position. Then Organize the wavelet coefficients in a 2D array, called the scalogram, where the horizontal axis corresponds to time and the vertical axis represents the scale parameter. By utilizing the scalogram, one can examine and visualize the signal's frequency content across various temporal resolutions or scales. There are libraries such as scipy, PyWavelets, and ssqueezepy, which can be used in Python to perform the CWT and convert a signal into a scalogram.

In our model, ssqueezepy library in Python is used to obtain the cwt of the signal. The CWT converts the 1D EEG signals into 2D scalogram images. The following figures show the EEG signal image converted to scalogram image.

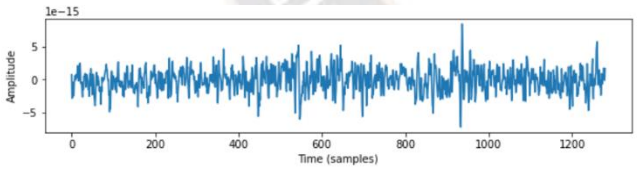

Figure 2. EEG signal for Healthy control (HC)

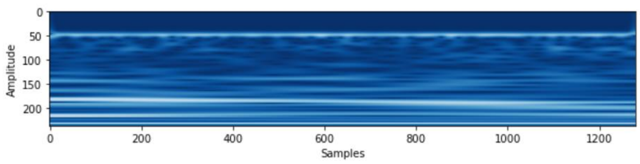

Figure 3. Scalogram Image for Healthy control (HC)

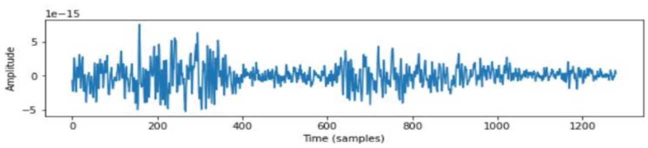

Figure 4. EEG signal for Mild Cognitive Impairment (MCI)

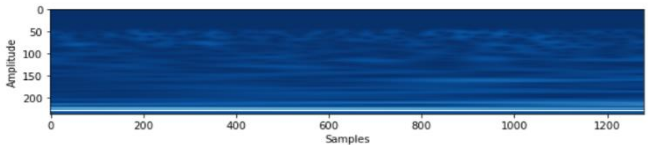

Figure 5. Scalogram Image for Mild Cognitive Impairment (MCI)

B. *Deep Learning Techniques*

A popular deep learning method, Convolutional Neural Network (CNN), is frequently employed for the purpose of image classification. Its main function is to extract features and classify them. In most cases, the CNN framework consists of three distinct layers: the convolution layer, the pooling layer, and the fully connected layer [24]. Feature extraction is facilitated by the convolution and pooling layers, whereas the fully connected layer is employed for classification purposes in CNNs. Although CNNs are suitable for classification tasks, their training process necessitates large amounts of data to achieve optimal performance. To overcome this, pre-trained models can be used, which have already been trained on a large dataset such as ImageNet, which consists of 1000 classes. These models do not require additional training and have become increasingly popular. The current study aimed to determine the most suitable pre-trained CNN model among VGG16, ResNet50, InceptionV3, and InceptionResnetV2 by conducting a comparative analysis.

1) Transfer Learning: Transfer learning refers to the approach of leveraging the knowledge gained by a pre-existing model to enhance the performance of a novel model for a distinct task. While the pre-trained model serves as the base model, fine-tuning involves training the new model on a new dataset to adapt to a different task. The size of the new dataset and the similarity of the data to the pre-existing model's training data and the available computational resources are crucial factors to consider during fine-tuning [25]. The success of fine-tuning the pre-existing model relies on the similarity of the new dataset to the original training dataset, with greater similarity resulting in improved performance.

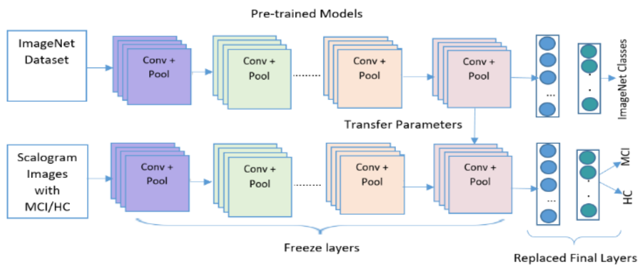

Figure 6. Transfer learning model without Fine-tuning.

In this study, four pre-trained models, VGG16, ResNet50, InceptionV3, and InceptionResnetV2, were used and all layers were frozen except for the fully connected (FC) layer.

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Additional FC layers were added, and the configuration is detailed in Table 1.

TABLE I. DESCRIPTION OF PRETRAINED MODELS WITH REPLACED FINAL LAYERS

Pre-trained model	No. of Layers	No. of parameters	Input Image size	Replaced final layers	No. of trainable parameters
ResNet-50	50	25,636,712	224 x 224	avg_pool, predictions	4098
InceptionResnetv2	164	55,873,736	299 X 299	avg_pool, predictions	3074
InceptionV3	316	23,851,784	299 X 299	activation_71, activation_75, max_pooling2d_3, mixed8	4098
VGG16	16	14,740,290	224 X 224	fc1, fc2, prediction	25602

2) Transfer Learning with Fine tuning pre-trained models: Fine-tuning a pre-trained model is achieved by adjusting specific layers of the model and adding new layers to adapt the model to a new task. The pre-trained model, which has already learned features from a large dataset, is used as a starting point. Some layers of the pre-trained model are frozen while others are unfrozen, allowing the new model to learn relevant features from a smaller dataset. The new layers are then trained on the smaller data set and fine-tuned to improve the performance. This technique enables the model to learn faster and with less data and computational resources than training a model from scratch [26]. The four pre-trained models are employed with varying learning rates and optimizers.

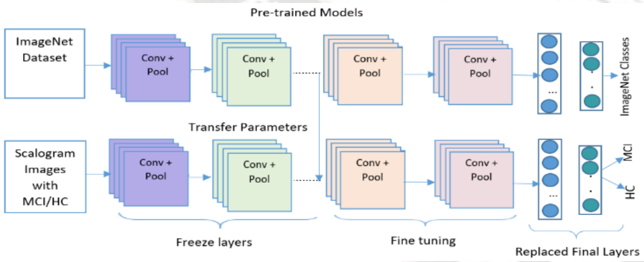

Figure 7. Transfer learning model with Fine-tuning.

TABLE II. FINE-TUNED TRANSFER LEARNING MODEL WITH REPLACED FINAL LAYERS

Pre-trained model	Replaced final layers	No. of trainable parameters
ResNet-50	avg_pool, predictions	4098
InceptionResnetv2	avg_pool, predictions	3074
InceptionV3	activation_71, activation_75, max_pooling2d_3, mixed8	4098
VGG16	fc1, fc2, predictions	25602

IV. EXPERIMENTAL RESULTS

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.

A. 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.

$$A = \frac{tp + tn}{tp + fp + tn + fn} \qquad (2)$$

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

$$P = \frac{tp}{tp + fp} \qquad (3)$$

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

$$R = \frac{tp}{tp + fn} \qquad (4)$$

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

$$F1 = \frac{2 \text{ x } [(P \text{ x } R)]}{(P + R)} \qquad (5)$$

B. Transfer Learning without Fine-tuning

To assess the performance of pre-trained models such as VGG16, ResNet50, InceptionV3, and Inception-ResNetV2, their fully connected layers were replaced and the resulting effectiveness was measured. Through the application of transfer

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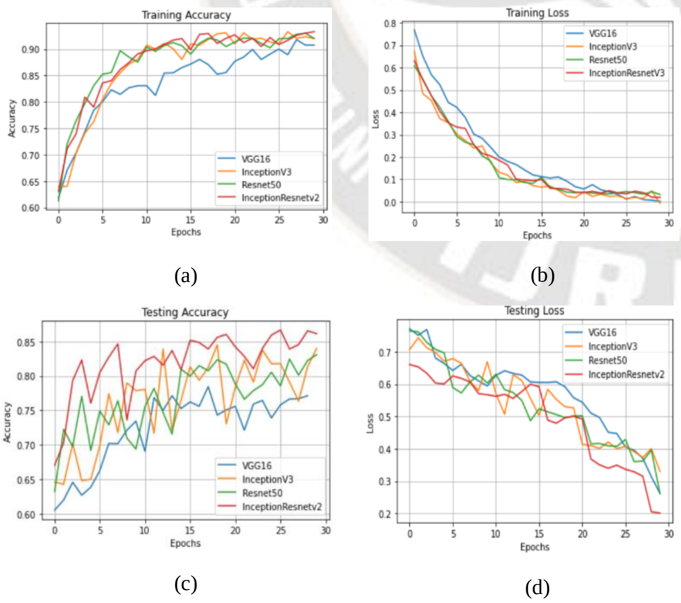
learning, it was determined that the InceptionV3 model exhibited superior performance, achieving the highest accuracy out of the four models that were evaluated.

Four pre-trained models were assessed by comparing their performance on 2D scalogram images that were generated from 1D EEG signals. The fully connected layers of these models were replaced and they were evaluated on test data. The training and testing accuracy and loss were determined over the course of 30 iterations, utilizing a batch size of 32. The "epoch" and "batch" are hyperparameters in the transfer learning process. Because of limitations in computer memory, the entire training dataset could not be processed at once, so it was divided into smaller batches that could be handled by the memory. These batches were processed one by one for training. A single pass through all batches is called an epoch, and this process is repeated multiple times for successful training. During the training process, the InceptionResnetV2 model exhibited the highest accuracy among the other three models. The InceptionV3 and Resnet50 models performed well, while the VGG16 model had poor performance, as depicted in Figure. 8(a). In Figure. 8(b), the training loss for each of the four models can be observed, where the InceptionResnetV2, InceptionV3 and Resnet50 models had low loss values, while the VGG16 model had high loss values compared to the other models. The testing accuracy and testing loss of the four models were displayed in Figure. 8(c) and (d), respectively. Fluctuations were observed for test data in all four models. The VGG16 model had very poor performance and the InceptionResnetV2 model performed effectively.



(a) (b) (c) (d)

Figure 8. (a) training accuracy, (b) training loss, (c) testing accuracy, (d) testing loss for pretrained Transfer Learning Models for 30 epochs

The transfer learning models were evaluated for their performance using various metrics such as accuracy, precision, recall and F1-score which are shown in Table 3.

TABLE III. CLASSIFICATION RESULTS FOR TRANSFER LEARNING MODELS

	Accuracy (%)	**Precision (%)**	**Recall (%)**	**F1-score (%)**
VGG16	78.50	90.24	65.53	75.92
ResNet50	83.29	94.69	78.53	85.85
InceptionV3	84.74	86.94	77.66	82.03
Inception-ResnetV2	86.66	81.85	87.47	84.56

The models were evaluated based on their accuracy, precision, recall, and F1-score, and Inception-ResnetV2 emerged as the best performer with an accuracy of 86.66%, precision of 81.85%, recall of 87.47%, and an F1-score of 84.56%. While ResNet50 achieved a higher precision of 94.69% and F1-score of 85.85% compared to the other models. The training time for the four models in seconds is also shown.

C. Transfer Learning with Fine-tuning

In this study, four different transfer learning techniques were fine-tuned by adjusting the parameters in the final layers of the model to adapt it to the new task. The performance of these techniques was evaluated using different optimizers and learning rates. An optimizer is an algorithm that modifies the characteristics of a neural network, such as weights and learning rate, to minimize loss and improve accuracy. The models were trained using a range of optimizers, including Adam, SGD, and RMSprop, with various learning rates(lr), such as: 0.0001, 0.001, 0.01, and 0.1. The results of these fine-tuned models were compared in Table 4.

TABLE IV. CLASSIFICATION TASK TO EVALUATE FINE-TUNED TRANSFER LEARNING MODELS

Models	**Optimizers**	**Learning Rate**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
VGG16	**Adam**	0.1	47.33	68.86	45.32	54.66
		0.01	62.45	56.66	60.02	58.29
		0.001	75.34	63.42	58.99	61.12
		0.0001	79.56	72.32	70.09	71.18
	SGD	0.1	80.13	72.16	74.44	73.28
		0.01	79.82	73.46	70.02	71.69
		0.001	72.33	69.56	67.32	68.42
		0.0001	70.02	71.33	69.73	70.52
	RMSPROP	0.01	40.02	93.22	41.32	57.73
		0.01	41.32	93.99	40.02	56.13
		0.001	56.99	60.09	65.45	62.65
		0.0001	62.32	67.87	62.76	65.21
ResNet50	**Adam**	0.1	52.65	79.86	50.41	61.80
		0.01	78.45	67.25	84.67	74.96
		0.001	91.08	95.13	87.39	91.09
		0.0001	96.69	96.66	96.24	96.44

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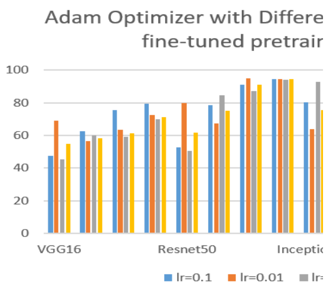
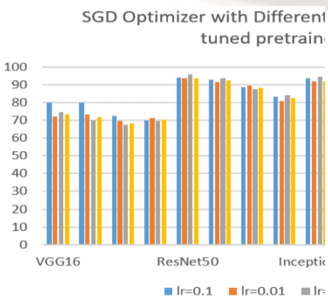
	SGD	0.1	93.84	93.58	95.58	93.58
		0.01	92.88	91.59	93.45	92.51
		0.001	88.74	89.38	87.44	88.39
		0.0001	83.33	80.75	83.90	82.29
	RMSPROP	0.1	47.99	100	47.99	64.77
		0.01	47.99	100	47.99	64.77
		0.001	87.33	81.67	91.11	86.09
		0.0001	93.63	91.15	95.37	93.21
InceptionV3	**Adam**	0.1	80.25	63.93	92.62	75.64
		0.01	70.91	51.10	81.33	62.76
		0.001	92.99	91.59	93.66	92.61
		0.0001	92.99	92.69	92.69	96.69
	SGD	0.1	93.41	91.81	94.31	92.15
		0.01	93.41	96.01	90.79	93.32
		0.001	83.12	88.71	78.78	83.45
		0.0001	71.33	63.71	73.09	68.07
	RMSPROP	0.1	47.99	100	47.99	64.77
		0.01	47.99	100	47.99	64.77
		0.001	92.67	92.92	91.90	92.40
		0.0001	96.05	97.35	94.48	94.90
Inception-ResnetV2	**Adam**	0.1	78.34	59.73	92.46	72.57
		0.01	89.75	87.16	90.90	88.99
		0.001	90.12	86.5	92.4	89.35
		0.0001	90.12	86.5	92.4	89.35
	SGD	0.1	89.49	92.24	91.14	91.68
		0.01	91.08	90.88	90.48	90.67
		0.001	84.92	84.73	83.99	84.35
		0.0001	70.50	56.63	75.96	64.88
	RMSPROP	0.1	55.62	100	51.95	68.37
		0.01	85.24	94.02	79.14	85.56
		0.001	86.94	85.17	87.30	86.22
		0.0001	90.33	88.49	91.11	89.53

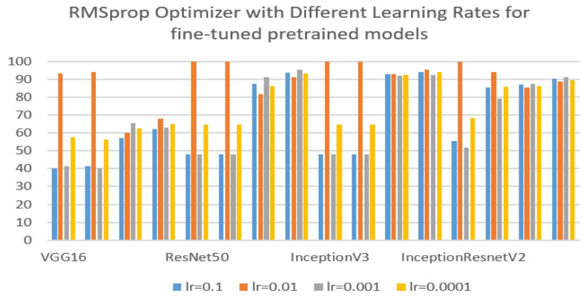
According to the data presented in Table 4, it appears that the Resnet50 model with the Adam optimizer and the InceptionV3 model with the RMSprop optimizer have The fine-tuned transfer learning model with the lowest learning rate of 0.0001 demonstrated superior classification results compared to the other models. The results suggest that RMSprop and Adam optimizers tend to be more effective at lower learning rates, while the SGD optimizer performs better with higher rates. The VGG16 model, in contrast, has lower performance compared to the other models when using Adam, RMSprop, and SGD optimizers.



(a)



(b)



(c)

Figure 9. Classification accuracy obtained for VGG16, Resnet50, InceptionV3 and InceptionResnetV2 with (a) Adam optimizer, (b) SGD optimizer and (C) RMSprop optimizer for lr=0.1, 0.01, 0.001 and 0.0001.

From Figure 9, it is evident that the VGG16, Resnet50, InceptionV3, and InceptionResnetV2 models, when fine-tuned with the Adam optimizer, achieve high accuracy using low lr0.0001. Additionally, the optimizer SGD is found to provide better accuracy for the VGG16 and Resnet50 models at a learning rate of 0.1, while the InceptionV3 model performs best at learning rates of 0.1 and 0.01. The InceptionResnetV2 model, on the other hand, achieves the highest accuracy at a lr=0.01. The optimizer, RMSprop also demonstrates good performance across all four models at a learning rate of 0.0001.

V. CONCLUSION

The core objective of this study is to use various deep learning pre-trained models, both without fine-tuning and with fine-tuning, to detect MCI and HC using dataset containing electroencephalogram signals. The EEG signal dataset is converted into scalogram images to improve the accuracy of detecting MCI and HC. The models are fine-tuned using transfer learning techniques to improve their performance. The classification accuracy of the VGG16, Resnet50, InceptionV3 and InceptionResnetV2 models, trained with Adam, SGD, and RMSprop optimizers, and different learning rates, is compared. The experiments conducted on the EEG signal dataset revealed that the Resnet50 and InceptionV3 models achieved the highest accuracy of 96.69% using the Adam optimizer with a lr=0.0001, and 96.05% using the RMSprop optimizer with a lr=0.0001. On the other hand, the VGG16 model exhibited the lowest performance compared to the other models.

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