Detection of Alzheimer's Disease by Using Time-Frequency Representations of EEG Signals with Deep Learning

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***Abstract*—Alzheimer's disease (AD) is a neurodegenerative disorder and the most common type of dementia. It leads to impairments in cognitive functions and seriously affects quality of life. Early diagnosis of the disease is crucial for effective treatment and management. This study proposes a new method using a modified ResNet18 CNN architecture to detect and monitor AD using electroencephalography (EEG) signals. The standard ResNet18 CNN architecture was simplified to use fewer layers and lower filter degrees to expedite the training procedures. In the proposed method, the scalogram images obtained using the Continuous Wavelet Transform (CWT) from 5 sec EEG segments of the AD and control groups are used as input to the modified ResNet18 CNN architecture. 2D time-frequency images of EEG segments are generated using both Bump wavelet CWT and the Short-Time Fourier Transform (STFT), for comparison. Calculated images are used to train the standard ResNet18, and modified ResNet18 CNN architectures to classify the EEG segments. Experimental results show that the CWT approach achieved higher performance compared to the STFT, and the proposed modified ResNet18 CNN architecture (93.74% accuracy) demonstrated more balanced performance than other architectures, exhibiting no overfitting, and completed the training much faster than other models, providing significant time savings.**

***Index Terms*—Alzehimer's dementia (AD), Electroencephalography (EEG), Short-Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), Deep Learning, CNNs.**

I. Introduction

Dementia is a neurological syndrome that usually develops due to brain disease and has a chronic or progressive structure. In this syndrome, impairments occur in memory, thinking, language, and other cognitive functions. Dementia affects mostly older people, and the rate of cases beginning before the age of 65 is only 2 percent. However, with age, the prevalence of dementia doubles every five years. Dementia is one of the main causes of disability in older age [1].

The World Health Organization (WHO) estimates that the number of people aged 60 and over will exceed 1 billion in 2020 and that this age group will reach 2.1 billion by 2050. As populations age, it is projected that the number of individuals living with dementia globally will increase from 55 million in 2019 to 139 million by 2050 [2]. Alzheimer's disease (AD) is the most common form of dementia. It accounts for 50-75% of dementia cases in individuals aged 65 and older and is the leading cause of death compared to other dementia syndromes. AD is a neurodegenerative condition characterized by a slow onset and progressive deterioration in behavioral and cognitive functions [3]. Early diagnosis of Alzheimer's disease is crucial for maintaining the patient's quality of life and for managing the disease. In this study, EEG data of patients diagnosed with early-stage Alzheimer's disease (AD) were examined. Various medical methods can be employed in the diagnosis of AD. Brain scans, such as magnetic resonance imaging (MRI) or positron emission tomography (PET), can be used to detect brain abnormalities associated with AD [1].

Electroencephalography (EEG) signals, which are used to detect electrical activity in the brain, are employed in the diagnosis of various medical and neurological conditions, including AD [4]. The EEG method is a highly advantageous technique for the diagnosis of AD because it provides real-time information, can detect subtle changes in brain waves associated with AD at an early stage, does not involve radiation, is cost-effective, non-invasive, accessible, and portable [5]. The literature contains numerous studies that utilize EEG techniques in the diagnosis and treatment monitoring of AD. Various decomposition techniques, such as Short-Time Fourier Transform (STFT) [6], Continuous Wavelet Transform (CWT) [7], Discrete Wavelet Transform (DWT) [8], and Empirical

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Mode Decomposition (EMD) [9] have been employed for the analysis of EEG data in AD patients. Researchers have proposed machine learning-based methods [9], [10], deep learning-based methods [11], [12], and hybrid methods (combining machine learning and deep learning) [6], [13] for the classification of AD patients.

In this study, images obtained from 5-second segmented EEG signals of 15 AD patients diagnosed with early-stage Alzheimer's disease and 11 healthy control volunteers are used as input in various CNN architectures to determine the most accurate approach to detect Alzheimer's disease.

II. ALZHEIMER'S DEMENTIA EEG DATA SET

In this study, EEG signals from 15 AD patients, diagnosed with early-stage Alzheimer's disease through neuroimaging techniques and diagnostic tests, and 11 healthy control volunteers were used. The EEG signals were recorded at the dementia clinic of the Neurology Department at İzmir Katip Çelebi University Faculty of Medicine. Among the 15 AD patients whose EEG signals were used, 8 are female and 7 are male, with an average Mini-Mental Test (MMT) score of 22 out of 30 and an average age of 64.53±8.47 years. The control group consisted of 5 females and 6 males, with an average age of 57.09±5.28 years. The signals were recorded from 19 channels at a sampling frequency of 200 Hz, using the Philips Alice-6 device, for approximately 30 minutes, in a resting state with eyes closed. Ethical approval for the EEG signals used in the study was obtained from the Clinical Research Ethics Committee of İzmir Katip Çelebi University, with approval dated 22.10.2020 and number 83.

The study used a Type II Butterworth bandpass filter to filter EEG signals, segmenting them into non-overlapping windows of 1000 samples. The signals are then subjected to STFT and CWT Bump transformations, and for each transformation separately, from 19 channels, 94,267 images were obtained from 15 AD patients, and 62,835 images were obtained from 11 control group individuals.

III. IMAGE REPRESENTATION OF EEG DATA USING TIME-FREQUENCY APPROACHES

A. Short-Time Fourier Transform (STFT)

The Short-Time Fourier Transform (STFT) is a traditional method based on the short-term processing of non-stationary signals to capture time-varying frequency content. STFT uses a sliding window to divide the signal into short-time, often overlapping segments. The Fourier transform of these short-time segments is calculated and the process is repeated until the entire signal is covered by windowing. The resolution of the resulting STFT varies depending on analysis parameters such as window size, window type, and amount of overlap. The square of the STFT's magnitude is called the "spectrogram", which is frequently used to estimate how the energy of a signal is distributed across the time-frequency (TF) plane [14].

In this study, EEG signals with a sampling frequency of 200 Hz were analyzed for 5-second segment durations (1000 samples). Hamming window and 50% overlap are used to obtain STFT representations of EEG segments. The window size is chosen to be 25% of the segment size.

B. Continuous Wavelet Transform (CWT)

The Continuous Wavelet Transform (CWT) is a method proposed to overcome the window length limitation in the STFT. Wavelet transform uses a variable window, where the resolution changes along the time-frequency plane to capture all the information contained in the signal [15]. The segmented data set is transformed from the time domain to the time-frequency domain by using CWT. The scalogram of the signal is calculated by squaring the absolute value of the CWT [16]. Mother wavelets in CWT represent time and frequency information simultaneously, allowing for understanding signal behavior at various scales. They differ in shape, length, frequency content, synchronization, time shifting, and scaling. The bump wavelet was used for time-frequency analysis due to its high-frequency resolution [15].

This study generates spectrogram and scalogram images from 200-Hz EEG signals utilizing STFT and CWT Bump time-frequency transformations, employing the Turbo color bar, and saving them in 2D RGB image format. The images are then fed into deep learning models.

IV. CLASSIFICATION OF EEG IMAGES USING CNN

Classical machine learning algorithms require complex feature engineering, requiring extensive exploration of original EEG data. Deep learning, a subset of machine learning, automates feature engineering using neural networks and hidden layers, saving time and energy [12]. Convolutional Neural Networks (CNNs) are a type of deep learning model that can learn and generate high-level information from low-level features, achieving superior performance in visual object recognition tasks without the need for handmade features [17].

Within the scope of this study, images obtained from EEG signals using STFT and CWT Bump time-frequency transformations were used as input in Convolutional Neural Network (CNN) architectures such as ResNet18 and modified ResNet18 to determine which method is more effective in diagnosing Alzheimer's disease (AD).

ResNet18 is an 18-layer CNN with shortcut connections, allowing for optimization and increased layers [18]. It has been widely used in studies, but a new model modified ResNet18, has been designed to optimize it for binary classification problems with fewer training sets. The proposed model, modified ResNet18, reduces the number of convolution layers from 17 to 9 and reduces the number of filters to 16, 16, and 32 compared to the original model. The design of this architecture aims to reduce training costs by reducing filters and enhancing binary classification accuracy compared to ResNet18.

A. Hyper-parameters Used in the Study

The study focused on optimizing deep learning architectures using hyper-parameters such as Adam Solver, Mini Batch Size, Max Epochs, Learning Rate, and L2 Regularization [19]. The Adam optimization algorithm was used for efficient

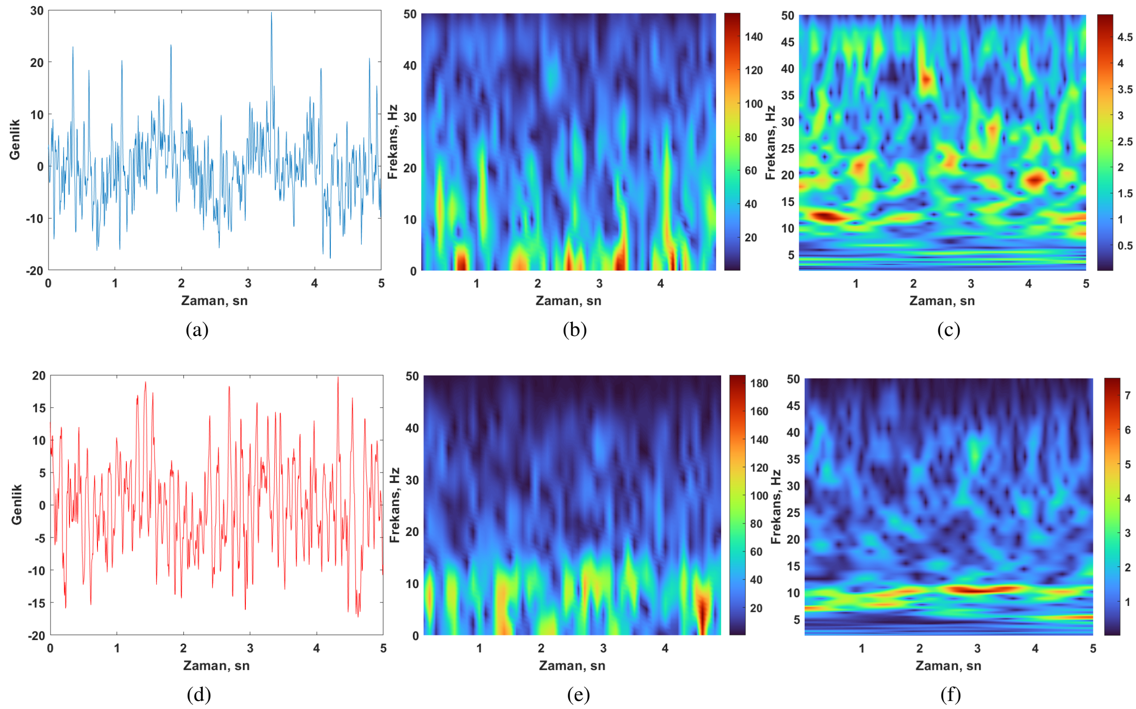


Fig. 1: 5-second electroencephalogram segment of the control subject (a) and the Alzheimer's patient (d) and related time-frequency representations; Short-Time Fourier Transform (b, e) and Continuous Wavelet Transform Bump (c, f)

calculations and large data sets. Mini-batch size was set to 64 and max epochs were set to 20 for all architectures. L2 regularization was applied to prevent overfitting.

B. Performance Metrics Used in the Study

Deep feature extraction is carried out in this study utilizing two distinct CNN architectures following the acquisition of the time-frequency representations of EEG segments. The deep learning models' accuracy in image classification is comprehensively assessed using a few key performance metrics. Performance metrics, such as accuracy (ACC), precision (PRE), sensitivity (SEN), and specificity (SPE), are utilized for performance evaluation based on the collected data [9].

V. Experimental Results and Discussion

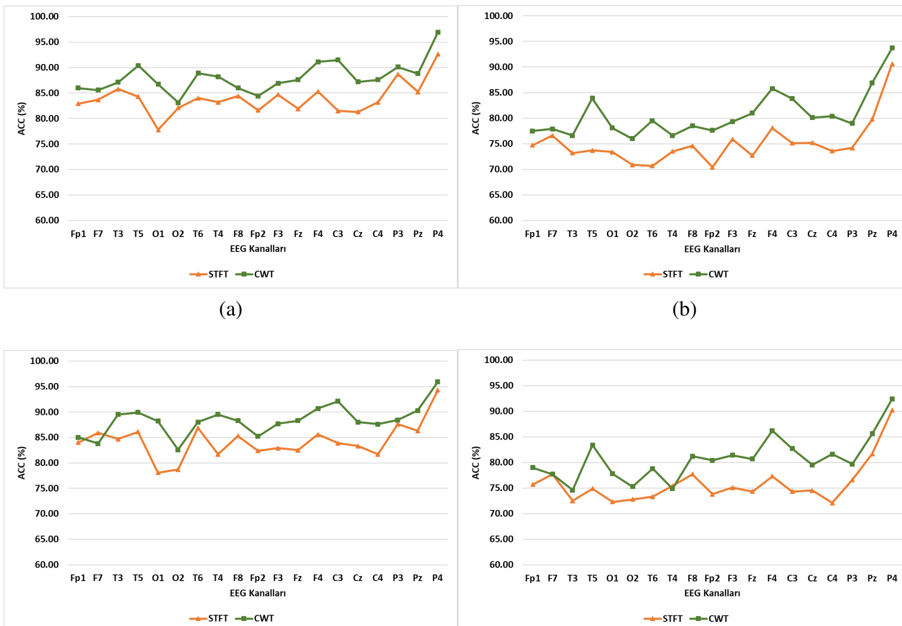
To diagnose AD patients, scalogram and spectrogram images are obtained from 5-second EEG segments obtained from 19 different channels of 15 AD patients and 11 healthy control volunteers using STFT and CWT Bump TF approaches. Example TF images obtained using the STFT and CWT Bump methods for one EEG segment from control subjects and AD are shown in Figure 1. Then, these obtained images are used as input in the ResNet18 and modified ResNet18 CNN architectures. These architectures include the convolution layer, batch normalization layer, activation function layer, maximum pooling layer, fully-connected layer, and Softmax layers. In the architectures, 70% of the images are divided for the training set, 15% for the validation set, and the remaining 15% for the test set.

Table I presents the performance metric results with the highest accuracy rates of all architectures, obtained with the STFT and CWT Bump approaches and averaged on a channel basis. According to the results in the table; the highest accuracy rates are obtained with the CWT Bump approach for both architectures. In terms of average validation results, the ResNet18 CNN architecture performs the best using the CWT Bump TF technique, with 88.76% PRE, 82.24% SPE, 91.77% SEN, and 88.11% ACC values. Similarly, among the average test results, with the CWT Bump TF approach, ResNet18 has the highest performance with 89.33% PRE, 83.15% SPE, 91.55% SEN, and 88.37% ACC values. On the other hand, the CWT Bump TF technique yields the best performance among the average validation results for the modified ResNet18 architecture, with metric values of 81.21% PRE, 68.56% SPE, 88.19% SEN, and 80.64% ACC. Similarly, the CWT Bump TF technique performed the best among the average test results, with metric values of 81.20% PRE, 68.36% SPE, 88.28% SEN, and 80.68% ACC. Figure 2 shows the graphical representation of channel-based validation (a) and test (b) accuracy results of TF approaches for both architectures. ResNet18 yields more successful results considering the validation ACC values; however, considering all results, modified ResNet18 is also significantly successful.

Table II displays the execution time and ACC values acquired during the training process of the top-performing TF methods for both architectures, depending on the channels that perform the best across five different brain regions. Based on

TABLE I: The performance evaluation results of STFT and CWT-based TF approaches across various CNN models and classifiers.

		Validation (%)				Test (%)			
CNN Models	**TF Approach**	**ACC**	**SEN**	**SPE**	**PRE**	**ACC**	**SEN**	**SPE**	**PRE**
ResNet18	STFT	83.91	88.20	76.82	85.41	83.76	88.62	77.26	85.69
	CWT	88.11	91.77	82.24	88.76	88.37	91.55	83.15	89.33
modified ResNet18	STFT	75.10	86.07	57.73	75.79	75.91	86.73	59.12	76.49
	CWT	80.64	88.19	68.56	81.21	80.68	88.28	68.36	81.20



(a) (b)

(c) (d)

Fig. 2: The graphical representation of channel-based validation and test accuracy results of TF approaches for ResNet18 (a-c) and modified ResNet18 (b-d).

these findings, ResNet18 (96.87%) by employing the CWT Bump technique is the architecture with the highest validation accuracy. Using the CWT method, the modified ResNet18 architecture (93.74%) performs worse than ResNet18 considering the ACC value. However, it is shown that modified ResNet18 is the architecture that finishes training the quickest considering the execution time. Time-saving is extremely beneficial in AD-CS classification since early detection is crucial to the treatment of Alzheimer's disease. Furthermore, the modified ResNet18 architecture's classification accuracy is not appreciably worse than ResNet18. Although the modified ResNet18 (ACC = 93.74%) has a relatively lower accuracy compared to ResNet18 (ACC = 96.87%), its high synchronization between the training and validation processes, its ability to provide more balanced performance, and in addition, it completes the training process in a much shorter time compared to ResNet18 make it a more reliable and consistent model for AD-CS classification. For these reasons, the modified ResNet18 architecture stands out as a more suitable and preferable alternative in terms of application.

VI. Conclusion

This study proposes a modified ResNet18 CNN architecture, which is obtained by simplifying the classical ResNet18 architecture, to diagnose Alzheimer's disease from EEG signals. The first step is to segment the AD and CS EEG data for five seconds. The segmented EEG signals are then transformed using STFT and CWT Bump methods to generate scalogram and spectrogram images. Following, the images are fed into the Resnet18 and modified ResNet18 architectures, and the performance metrics are utilized to identify the most accurate classification technique. Examination of the results shows that CWT Bump outperforms STFT.

In brain region-based evaluation; the best results for all architectures are obtained from the posterior region of the brain. In channel-based evaluation, the ResNet18 architecture, using the CWT Bump approach, provided better results compared to the other channels, with a validation ACC of 96.87% and a test ACC of 95.90% at the P4 channel located in the posterior region of the brain (given in Figure 2 and indicated in Table II).

TABLE II: Brain cluster-based classification results for STFT and CWT techniques and the two CNN models.

					Training Progress	
Brain Cluster	**CNN Models**	**TF Approach**	**Channel**	**ACC (%)**	**Max Epoch**	**Execution Time**
Anterior	ResNet18	CWT	F4	91.09	20	47 min 2 sec
	modified ResNet18	CWT	F4	85.85	20	26 min 44 sec
Central	ResNet18	CWT	C3	91.54	20	45 min 24 sec
	modified ResNet18	CWT	C3	83.83	20	26 min 58 sec
Temporal/Left	ResNet18	CWT	T5	90.42	20	47 min 21 sec
	modified ResNet18	CWT	T5	83.91	20	26 min 32 sec
Temporal/Right	ResNet18	CWT	T6	88.92	20	46 min 55 sec
	modified ResNet18	CWT	T6	79.49	20	26 min 46 sec
Posterior	ResNet18	CWT	P4	96.87	20	11 min 11 sn
	modified ResNet18	CWT	P4	93.74	20	5 min 24 sn

In this study, the classical ResNet18 architecture is modified to design a new architecture, modified ResNet18, with fewer layers and lower filter degrees. Although the modified ResNet18 architecture has a relatively lower ACC value (93.74%) compared to ResNet18 (96.87%), the training progress results (given in Table II) indicate that it exhibits a balanced and successful performance without overfitting compared to ResNet18. Additionally, it saved significant time by completing the training process much faster. Considering the critical importance of early diagnosis for Alzheimer's disease, the modified ResNet18 architecture's superior performance in terms of both timing and balanced results makes it stand out as a more reliable and consistent model for AD-CS classification.

As a result, this study presents a method for classifying scalogram images obtained from EEG data using the modified ResNet18 architecture. Evaluation of the results revealed that the modified ResNet18 CNN can successfully extract time-frequency features, identify significant patterns in EEG data, and, when time and performance are taken into account, the architecture's training process performs significantly faster, more successfully, and more balanced than ResNet18. These findings are promising for detecting and classifying EEG differences between AD and CS. The high classification accuracy and efficiency obtained in the proposed method are important for usability in biomedical applications. In future studies, the dataset size will be expanded with records from more AD patients and control group participants, the model's performance will be tested with different disease stages (early, intermediate, advanced), and the applicability of the model in diagnosing other neurodegenerative diseases will be investigated.

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