EVENT-SPECIFIC EEG-FNIRS FEATURE FUSION FOR ALZHEIMER'S DISEASE CLASSIFICATION

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ABSTRACT

Alzheimer's disease (AD) remains a significant challenge in neurological disorders, necessitating advanced diagnostic techniques for early detection and intervention. This study presents a novel approach for AD classification utilizing a combination of electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) signals. The distinctive characteristics of the cognitive tasks employed in data acquisition underscore the need for task-specific feature extraction insights. To this end, we propose an innovative event-specific feature extraction method that adapts to the unique attributes of each task and signal. By tailoring feature extraction to the inherent characteristics of each task, we achieve maximal information extraction, thereby elevating classification performance. Our methodology employs Recursive Feature Elimination with Cross-Validation, which progressively deletes features with low importance from the model. This iterative process generates the essential features after the feature extraction. The EEG-fNIRS feature fusion capitalizes on their complementary nature, enhancing the discriminatory power of the classification model. Also, in addition to the resting state data usually used for AD classification, we used data collected through three cognitive tasks to identify rich features of AD patients. Our method demonstrates significant promise in effective diagnosis with varying cognitive statuses – healthy controls, mild cognitive impairment, and AD patients.

Index Terms— Alzheimer's disease, Electroencephalography, Functional near-infrared spectroscopy, Feature fusion, Machine-learning

1. INTRODUCTION

Alzheimer's disease (AD), the predominant form of dementia, is characterized by a profound deterioration in memory, language proficiency, and problem-solving capabilities, leading to substantial disruptions in daily functioning. It progressively erodes memory, cognitive functions, and the ability to execute routine tasks. Given the absence of effective treatments for AD, early detection is paramount for prompt intervention and enhanced disease management. Prior investigations [1–8] employed various datasets to diagnose the stages of AD, with medical data-driven studies making notable strides in AD classification. Typically, AD is classified into three stages: Healthy Controls (HC), Mild Cognitive Impairment (MCI), and AD, with many studies [7, 8] adopting this three-level categorization to detect the disease.

Functional Magnetic Resonance Imaging (fMRI), a specialized MRI scan variant, has been extensively utilized in AD diagnosis [5–7]. This non-invasive technique measures alterations in brain blood flow using a potent magnetic field and radio waves. Active brain regions exhibit increased blood flow to meet heightened energy requirements, a phenomenon detected by fMRI. Consequently, fMRI offers detailed spatial images pinpointing brain regions involved in specific activities. Nonetheless, fMRI deployment is accompanied by drawbacks such as cost, time consumption, and the need for patient immobility, potentially deterring some individuals. As a result, there is a growing interest in leveraging cost-effective, rapid, portable, and motion-tolerant tools like Electroencephalography (EEG) and functional Near-Infrared Spectroscopy (fNIRS) for AD diagnosis.

EEG is a non-invasive technique to record the brain's electrical activity via electrodes on the scalp. By directly capturing the brain's electrical signals, EEG boasts superior temporal resolution compared to fMRI and PET scans, facilitating the detection of changes occurring within milliseconds. Conversely, fNIRS represents another non-invasive avenue for gauging shifts in hemoglobin concentration linked to brain activity. Based on near-infrared light, fNIRS discerns absorption patterns in oxygenated and deoxygenated hemoglobin – the primary oxygen carrier in blood – while the remaining light is reflected. By measuring the returning light, it is possible to estimate the brain's blood oxygen levels, thereby indirectly measuring brain activity. AD clas-

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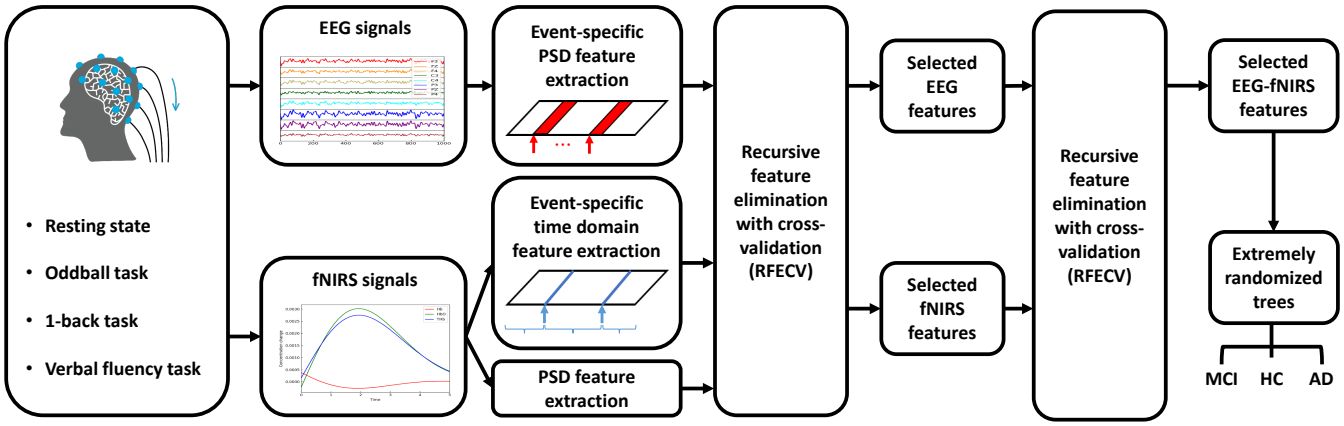

Fig. 1: Overview of the proposed method's framework. It includes an event-specific feature extraction method tailored to the task and data characteristics, followed by the selection of valuable features for AD classification using RFECV.

sification studies utilizing EEG and fNIRS data have already been proposed. Several EEG-based methods [9, 10] have successfully diagnosed patients with normal cognitive function and those with MCI or AD patients with precision. Also, fNIRS-based methods [11, 12] have shown that the fNIRS signal has the potential to provide knowledge related to AD. Recently, EEG-fNIRS hybrid data was used to classify the stages of AD. [13] introduced an fNIRS-constraint EEG source localization technique. This study collected EEG-fNIRS signals on a digit verbal span task and demonstrated that the two modalities could complement each other by leveraging fNIRS's high spatial resolution characteristics in analyzing EEG signals. [14] utilized the Rey-Osterrieth complex figure and Raven progressive matrices for collecting the dataset and calculated sample entropy from the five bands of the collected EEG, two fNIRS hemoglobin, and ten conditional entropy between them. Calculated entropy was used for multivariate data-driven analysis, classifying AD and healthy patients by the General Linear Model. [15] presented a similar method to that of [14] with EEG-fNIRS signals recorded in a resting state. [16] classified four stages of AD based on the random digit encoding-retrieval task. They developed the feature selection strategy to get the essential features for classification. However, these studies focused on binary classification between AD and HC stages or used one type of task when recording the EEG-fNIRS data.

In this work, we propose a novel strategy for Alzheimer's disease classification by integrating EEG-fNIRS hybrid data. Unlike previous methods, we utilize multiple cognitive tasks for collecting the EEG and fNIRS signals. We introduce event-specific feature extraction, which considers the unique attributes of each cognitive task and signal to enhance the discriminative power of our model. Also, we select the essential feature from EEG-fNIRS event-specific hybrid features by employing Recursive Feature Elimination with Cross-Validation (RFECV) [17]. Our overall framework is depicted in Fig.1. We evaluate the proposed strategy using three metrics. Our results demonstrate the effectiveness of the EEG-fNIRS hybrid feature fusion strategy for AD classification and underscore the contribution of employing various cognitive tasks to enhance classification performance.

2. METHOD

2.1. Dataset Description

In this study, we employ a dataset of EEG and fNIRS signals from 144 participants gathered from [18, 19]. The dataset encompasses 63 HC, 46 MCI, and 35 AD patients. These participants completed four tasks: resting state, oddball task, 1-back task, and verbal fluency task. The resting state task involved participants sitting while focusing on a stationary white cross at the center of a black screen for 60 seconds. The other three cognitive tasks were preceded and followed by a 30-second rest period. During the oddball task, a circle (0.5 seconds) and an empty screen (1-1.5 seconds) alternated on the black screen. The circle appeared in two colors: yellow (target), which required pressing the enter button, and blue (non-target), which did not necessitate any response. For the 1-back task, a random number from 1 to 3 (1 second) and an empty screen (1-1.5 seconds) alternated on the black screen. Like the oddball task, participants pressed the enter button when the same number appeared consecutively. The verbal fluency task comprised three phonemic and three semantic tasks, each separated by a 30-second rest period. In the phonemic task, participants generated words starting with a given letter, while the semantic task required producing words related to a provided category.

EEG and fNIRS signals were recorded simultaneously for all tasks. The EEG signal is 32 channels, and the sampling rate is 500 Hz. The fNIRS signal is six channels, and the sampling rate is 8 Hz. From the fNIRS signal, three signals were derived from each signal: oxyhemoglobin (HbO), de-

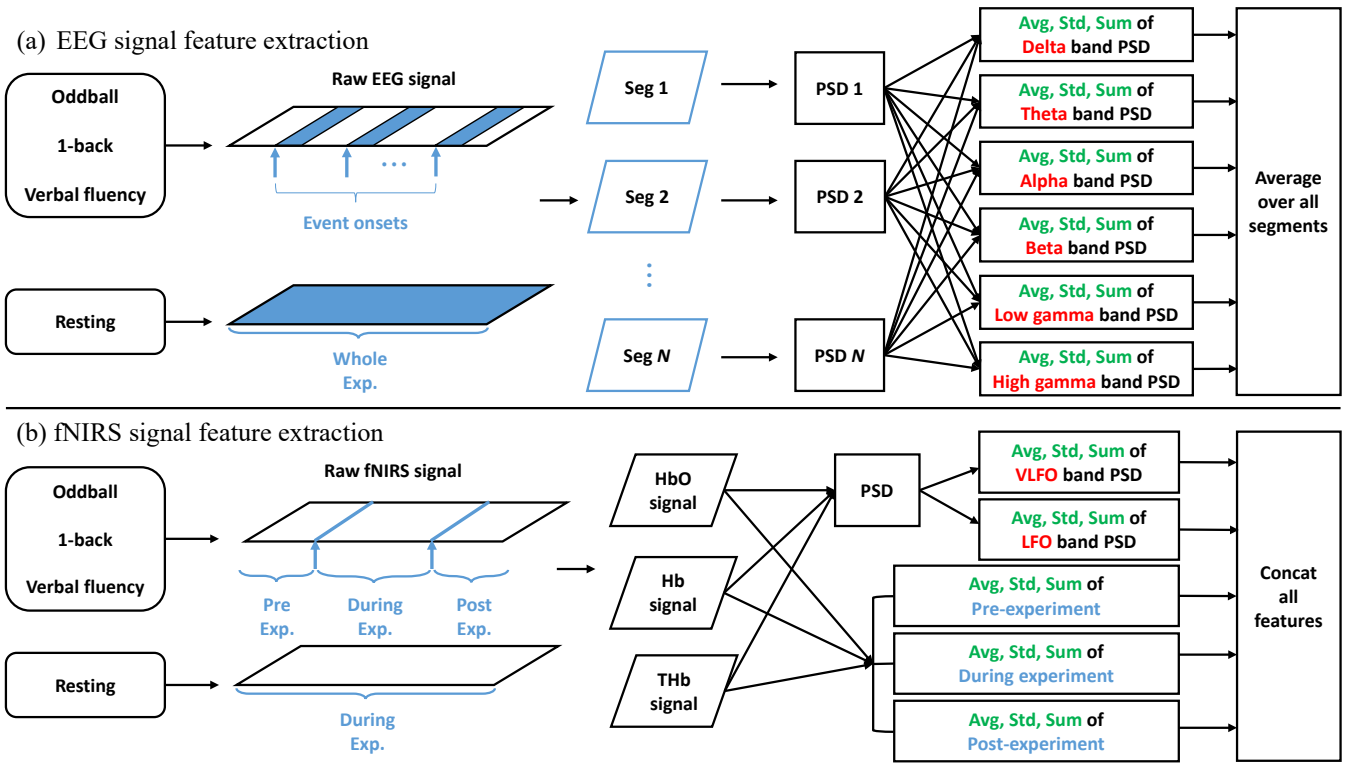

Fig. 2: Overview of feature extraction for EEG and fNIRS signals. (a) Segmentation of EEG signal for cognitive tasks (oddball, 1-back, and verbal fluency) and utilization of the entire sequence for feature extraction during the resting task (absence of events). Each segment is then processed into frequency domains via PSD and further divided into specific bands. (b) For fNIRS signals in cognitive tasks, segmentation into pre-, during-, and post-Exp phases, and for the resting task, treatment of the entire signal up to the during-Exp phase. Following segmentation, calculation of average, standard deviation, and summation of each segment. Similar to EEG, the fNIRS segments are transformed into frequency domains and subdivided into VLFO and LFO bands.

oxyhemoglobin (Hb), and total hemoglobin (THb=HbO+Hb) are used in the experiment.

2.2. Data Preprocessing

The fundamental preprocessing procedures are undertaken before feature extraction from the raw EEG and fNIRS signals acquired during the four tasks. In order to eliminate artifacts and noise from the signals, a 5th-order Butterworth band-pass filter is administered. The raw EEG signals undergo filtration within the primary frequency range of brainwaves (1-40Hz), while the raw fNIRS signals are subjected to filtration within 0.01-0.15Hz to eliminate respiratory and cardiac signals.

Subsequently, baseline corrections are executed on three cognitive tasks (oddball, 1-back, and verbal fluency) to enhance the discernibility of signal fluctuations stemming from events. This entails deducting the average signal intensity during a 30-second resting interval preceding the initiation of each task from the entirety of the signal.

2.3. Event-Specific Feature Extraction

The four tasks utilized to collect EEG and fNIRS signals exhibit distinct characteristics. Therefore, features with insufficient task-specific knowledge are generated when a common feature extraction method is used for all tasks. To address this, we introduce a task-specific feature extraction technique tailored to the unique attributes of each task, thereby capturing maximum information. Furthermore, during the feature extraction process, the inherent signal traits of EEG and fNIRS are meticulously considered in each dataset.

Excluding the resting task, there is a *trigger* in which the participant performs a specific objective: in oddball when a yellow circle appears; in 1-back, when the same number appears twice; and in verbal fluency, six actions are performed in the entire test. We define the *trigger* moment in each task as an *event*. Here, we cut segments when each *event* occurs and use each segment for feature extraction, not the entire signal. The EEG signal segmenting process is depicted in Fig. 2(a). For the oddball and 1-back tasks, there are 28 events in one action, so we generate 28 segments by dividing 5 sec-

onds from each event onset point. The verbal fluency task has six events (three phonemic and three semantic actions), each taking 30 seconds. Therefore, we generate six segments by cutting 30 seconds from each event onset point. For the resting task, the entire 60 seconds signal is treated as a single segment due to the absence of an event. After generating segments, we extract related features per frequency band from EEG signals by adopting Power Spectral Density (PSD). PSD transforms a signal from the time domain to the frequency domain to measure the signal's power at different frequencies. This is estimated using Welch's method [20], which splits the entire signal into smaller overlapping windows, applies the Fast Fourier Transform (FFT) [21] to each window to compute the power spectrum, and then averages them to estimate the PSD of the entire signal. The PSD of each segment is divided into six frequency bands (Delta: 1-4Hz, Theta: 4-8Hz, Alpha: 8-14Hz, Beta: 14-30Hz, Low gamma: 30-40Hz, High gamma: 40-50Hz), and average, standard deviation and the sum of each band power are computed. Then, each of the three statistical features per frequency band is averaged for all segments, extracting 18 features (6 bands × 3 statistics) per signal from a single electrode. Finally, the EEG feature extraction method is applied to 32 electrodes and four tasks, extracting the 2304 EEG features (4 tasks x 32 channels x 6 bands x 3 statistics) per subject.

Unlike EEG, which directly measures the brain's electrical activity, fNIRS indirectly measures brain activity through changes in cerebral blood flow, causing a delay in detection. However, since this delay can vary depending on the equipment and situation, it is not easy to analyze fNIRS signals for a short term immediately after an event occurrence, as with EEG. Therefore, fNIRS features are extracted from the entire signal in two ways. As shown in Fig. 2(b), we first calculate statistical features in the time domain. Each hemoglobin signal (HbO, Hb, THb) is split into three parts: a 30-second resting period before the start of the task (Pre-Exp.), the entire task duration (During-Exp.), and a 30-second rest period after the end of the task (Post-Exp.). Then, we calculate the average, standard deviation, and the sum of the raw signal of each part. Resting tasks, in particular, lack distinct start and end points; therefore, we utilize the entire signal for the extraction of time domain features. The second method involves frequency domain analysis using PSD. PSD of each of the three types of hemoglobin signals collected from each fNIRS channel is computed, and each PSD is categorized into two frequency bands: the Very Low Frequency Oscillations (VLFO: 0.01-0.04Hz) and the Low Frequency Oscillations (LFO: 0.04-0.15Hz). Then, the average, standard deviation, and sum of the power for each band are extracted as features. Finally, the two fNIRS feature extraction methods are applied to signals from 6 channels and four tasks, extracting a total of 972 fNIRS features (3 cognitive tasks × 6 channels × 45 statistics + 1 resting × 6 channels × 27 statistics) per subject.

2.4. Feature Selection and Classification

Through feature extraction, we create features specific to each task and consider the characteristics of the raw signal. We improve performance by selecting features closely related to AD classification from the generated features. Hence, we utilize Recursive Feature Elimination with Cross-Validation (RFECV) [17] to curate the most advantageous feature set for the classification task. RFECV is a method for feature selection that iteratively eliminates the least essential features until a deterioration in model performance is observed. The process initiates with the model being trained using all available features. Subsequently, the feature with the lowest importance – denoting its relative contribution to the model's predictive performance – is eliminated. The model is subsequently re-trained using the remaining features. This iterative procedure continues, with each step's performance evaluated through stratified cross-validation. Eventually, the most discriminative features, yielding the highest classification performance, are selected as the optimal feature set. As shown in Fig. 1, we first select features by applying RFECV to EEG and fNIRS features, respectively. Then, the two selected features are concatenated, and RFECV is applied once more to create EEG-fNIRS hybrid features. Inspired by [16], we introduced two-stage feature selection; this step helps identify the most relevant features across both modalities, potentially capturing complementary information that could be more predictive of Alzheimer's disease classification. In short, our proposed feature fusion strategy leverages the unique characteristics of cognitive tasks and EEG-fNIRS signals to extract influential features for AD classification.

After the feature selection, we adopt the extremely randomized trees classifier (ExtraTreesClassifier) for classification. ExtraTreesClassifier is fast due to randomized node splitting and has a low variance to prevent overfitting. The overall structure of the proposed design is shown in Fig. 1.

3. EXPERIMENTS

3.1. Implementation Details

We utilized datasets from [18, 19] to assess our method, comprising 63 HC, 46 MCI, and 35 AD participants. EEG and fNIRS signal collection is detailed in Section 2.1.

In our experiments, we used a 5-fold cross-validation approach. To circumvent redundancy with the cross-validation utilized in RFECV, we shared the validation set between RFECV and the training-test process. The ExtraTreesClassifier employed 100 estimators. Performance assessment and validation of experimental results were conducted using accuracy, F1 score, and AUC metrics. We use each class's average value of the F1 score and AUC.

Table 1: Ablation study of the modality and cognitive task.

Modality		Tasks				Accuracy	F1 score	AUC
EEG	fNIRS	Resting	1-back	Oddball	Verbal fluency			
✓	✓	✗	✓	✓	✓	0.8047	0.8095	**0.9151**
✓	✓	✓	✗	✓	✓	0.7845	0.7830	0.9030
✓	✓	✓	✓	✗	✓	0.7362	0.7440	0.8741
✓	✓	✓	✓	✓	✗	0.7357	0.7497	0.8798
✓	✗	✓	✓	✓	✓	0.7079	0.7002	0.8847
✗	✓	✓	✓	✓	✓	0.6345	0.6336	0.7349
✓	✓	✓	✓	✓	✓	**0.8126**	**0.8209**	0.9149

Table 2: Performance comparison of the classifiers

Classifier	Accuracy	F1 score	AUC
ExtraTrees	**0.8126**	**0.8209**	**0.9149**
SVM	0.6808	0.6838	0.8120
Random Forest	0.7360	0.7465	0.9088
MLP (DNNs)	0.7365	0.7366	0.8834

Table 3: Performance comparison of the feature extraction and selection method from Cicalese *et al.* [16]. * means re-implemented results.

FE		FS	Accuracy	F1 score	AUC
EEG	fNIRS				
Ours	Ours	Ours	**0.8126**	**0.8209**	**0.9149**
Ours	[16]*	Ours	0.6855	0.6924	0.8359
[16]*	Ours	Ours	0.6894	0.6753	0.8702
[16]*	[16]*	Ours	0.6975	0.6675	0.8777
[16]*	[16]*	[16]*	0.5944	0.5944	0.6890
Cicalese *et al.* [16]			0.7931	0.7600	-
Ho *et al.* [22]			0.7101	-	-
Perpetuini *et al.* [14]			-	-	0.8800

3.2. Results

This work aimed to efficiently categorize individuals according to their AD stage using hybrid EEG-fNIRS features. Using our proposed feature fusion strategy, we achieved the highest performance on the top 29 features, including 22 EEG and seven fNIRS features. When using different data in Tables 1 and 3, hybrid features from the data were separately generated to evaluate classification performance.

We undertook an ablation study to discern the impact of each task on classification performance. The influence of cognitive tasks is outlined in Table 1 (rows 1-4, 7). Optimal performance was attained when signals from all tasks were included. Notably, the resting task exhibited minimal influence, resulting in marginal performance degradation. In contrast, omitting tasks demanding higher-dimensional cognitive abilities—such as the oddball or verbal fluency task—led to a pronounced decline in performance. Experimental results show that the influence of each task is different, thus proving the necessity of utilizing signals from various tasks to contribute to the classification of AD.

Furthermore, we evaluated whether EEG and fNIRS signals improve AD classification performance. As indicated in Table 1 (rows 5-7), the omission of EEG features resulted in a decline of 22% in accuracy and 23% in F1 score. Similarly, excluding fNIRS features led to a reduction of 13% in accuracy and 15% in F1 score. This demonstrated that our EEG-fNIRS hybrid features extraction and selection method is a practical feature fusion strategy for a dataset consisting of the resting and three cognitive tasks. Also, utilizing EEG-fNIRS hybrid signals outperforms using a single signal, demonstrating that these two signals mutually complement each other and positively impact AD classification.

To demonstrate the ExtraTreesClassifier's suitability for our task, we conducted additional experiments with SVM, Random Forest, and MLP (DNNs) classifiers. We used the same hybrid features for all classifiers. As shown in Table 2, the ExtraTreesClassifier achieved the best performance across all metrics. It measures feature importance, is compatible with RFECV, and prevents overfitting through random feature selection and splits.

The comparative analysis was conducted using a previous research methodology to compare the efficacy of the proposed approach. Cicalese *et al.* [16] represented an EEG-fNIRS hybrid feature-based approach for AD classification, resembling our methodology. For EEG signal feature extraction (FE), [16] employed 2-second windows across the entire signal. Additionally, fNIRS signals were segmented into 3-second windows, with averages of HbO and Hb signals utilized. The final hybrid feature in [16] was generated through

a feature selection (FS) method based on the Pearson correlation coefficient. As reported in Table 3, our feature extraction and selection method outperformed the approach presented by [16]. Specifically, the experimental results showcased the effectiveness of the event-specific feature extraction method, which considers the characteristics of EEG and fNIRS signals and cognitive tasks. Additionally, the experimental results showed that performance was severely degraded in all metrics without RFECV. That indicates that RFECV is a suitable feature selection method in an environment where the primary objective is classification.

Alzheimer's disease-related papers often involve sensitive patient information, leading to a predominance of private datasets. Moreover, the lack of open-source code of proposed methods in many papers is also a common hurdle. Although all methods use their own dataset, we attach the results of the recent EEG-fNIRS data-based Alzheimer's disease classification methods [14, 16, 22] to compare performance. Table 3 (rows 6-8) shows that our method outperformed in all metrics. This demonstrates that the proposed strategy is competitive compared to other methods.

4. CONCLUSION

In this study, we introduced an innovative approach for classifying Alzheimer's disease using hybrid EEG-fNIRS data. Our method considered the variability in cognitive tasks and the inherent characteristics of multi-modal data. By implementing event-specific feature extraction, we leveraged the attributes of both tasks and signals to enhance classification accuracy. Integrating EEG and fNIRS data significantly improved the accuracy and robustness of our model. Through extensive experiments, we validated the substantial contribution of signals from multiple tasks to successful classification. These findings promise to advance diagnostic strategies and interventions for this challenging neurological disorder.

5. ACKNOWLEDGMENT

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