Mild Cognitive Impairment Detection with Machine Learning and Topological Data Analysis Applied to EEG Time-series in Facial Emotion Oddball Paradigm

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Abstract— **We report a novel approach to dementia neurobiomarker development from EEG time series using topological data analysis (TDA) methodology and machine learning (ML) tools in the 'AI for social good' application domain, with possible following application to home-based point of care diagnostics and cognitive intervention monitoring. We propose a new approach to a digital dementia neurobiomarker for early-onset mild cognitive impairment (MCI) prognosis. We report the best median accuracies in a range of upper 85% linear discriminant analysis (LDA), as well above 90% for linear SVM and deep fully connected neural network classifier models in leave-one-out-subject cross-validation, which presents very encouraging results in a binary healthy cognitive aging versus MCI stages using TDA features applied to brainwave time series patterns captured from a four-channel EEG wearable.**

Clinical relevance— **The reported study offers an objective dementia early onset neurobiomarker prospect to replace traditional subjective paper and pencil tests with an application of EEG-wearable-based and topological data analysis machine learning tools in a possibly successive home-based point-of-care environment.**

I. INTRODUCTION

The growth of dementia patient numbers significantly impacts healthcare expenditures worldwide. Approximately 50 million elderly worldwide suffer from a dementia spectrum late age-related neurocognitive disorders, as reported by the World Health Organization (WHO) [1] and the number will triple soon [2]. Early onset MCI is when an individual experiences cognitive decline more significant than expected for their age but does not yet meet the criteria for dementia [3]. Common symptoms of early onset MCI include memory problems, difficulty with language, problems with attention and concentration, and difficulty with problem-solving and decision-making [3]. The growing aging societies crisis summons doable deployment of artificial intelligence (AI) and especially ML tools to enhance rapid diagnostics for consequential late age cognitive state evaluation and preservation with "digital pharma" or "beyond a pill" non-pharmacological-therapeutical (NPT) strategies [4].

We document a study with Japanese elderly participants using a wearable EEG device. MUSE EEG appliance (InterAxon Inc., Toronto, Canada) demonstrated its potential feasibility in non-clinical or even for home-based environments [5], [6], [7], [8], [9], [10], [11]. Dry–electrode EEG designs are known for amplified noise in captured EEG compared to clinical-grade instruments. To handle the extra noise in recorded EEG, we utilize a previously developed method by the authors [12], [13], which employs data-driven empirical mode decomposition (EMD) to remove eye-blinks or muscle movement-related artifacts.

We employ a previously developed task by the authors of emotional identification short-term memory oddball paradigm [9]. The obtained EEG recording regards an objective evaluation of working/short-term memory during facial emotion encoding and decoding. We next apply a topological data analysis (TDA) approach [14] to EEG time series to demonstrate contrasts between healthy aging cognition and mild cognitive impairment (MCI) in elderly participants. The following methods sections explain the proposed experimental procedure's motivation and details. We also involve several shallow and deep machine learning classification strategies to rank the EEG recordings as healthy cognitive aging versus MCI. The results interpretation and prospective application discussion conclude the article.

II. METHODS

We document EEG experimentations with elderly Japanese participants who partook in our study conducted in the RIKEN Center for Advanced Intelligence Project (AIP), Tokyo, Japan. The RIKEN Ethical Committee has approved the investigation for Experiments with Human Subjects, permission number Wako3 30-28(4), and complies with The Declaration of Helsinki. In the current research project, 33 elderly take part (22 females; mean participant age of 73.6 ± 4.95 years old; 15 MCI and 15 healthy aging cognition). The elderly Japanese participants were drawn from Silver Human Resources Center and Honobono Laboratory, Japan. All participants supplied documented informed consent and accepted financial compensation.

A. EEG Experiments

Similarly, as in the previously reported study [9], a participant sits in front of a computer screen and observes different emotional facial videos drawn from a Mind Reading library [15]. As in the classical oddball paradigm, the participant's task is to memorize a single short facial video portraying an emotional expression, and next, a random

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series of eight emotional displays by the same actor follows. The healthy cognitive aging participants are expected to mentally recall previously memorized emotional expressions, while those with MCI might have problems with recalls and inhibition of the distracting non-target stimuli. Our project hypothesis is that brainwave dynamics differences captured in EEG can be elucidated with TDA and machine learning tools. In the pre-pandemic study in 2019 [6], [7], [8], we evaluated the Japanese elderly participants with Montreal Cognitive Assessment (MoCA) test [16] and MoCA score 25 and below (MoCA ≤ 25), indicated an MCI onset.

B. EEG Recording, Preprocessing and Feature Extraction

The MUSE 2016 wearable EEG headband (InteraXon Inc., Canada) employed in our study permits suitable electrical brain activity monitoring from preset dry electrodes $AF7, AF8, TP9$, and $TP10$, with a ground and reference electrodes on a forehead [5]. We operate an in-house EEG recording environment running a muse-lsl [5] library in Python, which communicates with MAX backend (by Cycling '74, USA) patches for synchronized video facial stimuli exhibition. A 50 Hz notch filter is also applied to remove power line interference (a local power grid frequency in Tokyo) and a subsequent bandpass–filter within $1 \sim 40$Hz unrelated baseline drifts and high-frequency noises. In order to dismiss muscle and eye movement-related artifacts usually contaminating EEGs, we utilize a formerly invented empirical mode decomposition (EMD) methodology [12], [13]. In the EMD application to EEG, all the channels are first decomposed into intrinsic mode functions (IMF). Next, we reject all the IMFs that exceed the 100 μV threshold before the final signal reconstruction from clean/subthreshold IMFs. We implement the above EMD-based EEG denoising procedures in PyEMD ver.1.4.0 [17]. Topology in mathematics studies shapes and spaces that are hard to convey visually [18]. Topology application in data analysis [19] allows for describing and classifying noisy and highly-dimensional datasets by extracting topological invariants distinguishing the complex datasets [20]. Among the many topological methods developed for data analysis [20], [18], [19], a persistent homology is the most often used [14]. Persistent homology permits the construction of descriptors of the shape of a point cloud, and it permits cataloging the existence of different structural features, such as connected components, cycles, and voids. In the current project, we utilize the persistent homology, a number of cycles, and normalized persistence entropy features, as developed in [14], to describe the noisy point of clouds generated from four-channel EEG traces recorded operating a MUSE wearable during facial emotion oddball task performed by elderly participants in the presented study.

C. Supervised Clustering and Classification

In the documented study, we first visualize the TDA features with a uniform manifold approximation and projection (UMAP) [21], a powerful supervised dimensionality reduction technique employing a topological manifold analysis. In a final classification approach employing a leave-one-out-subject cross-validation (LOOSCV) technique allowing for keeping in each cross-validation step all data of a single subject and training a model using all the remaining subjects; thus, the procedure could be repeated for all the available subjects, and final accuracies are concatenated and elucidation with median and confidence intervals as discussed in the results section. In the following shallow and deep machine learning models, as available in the scikit-learn ver. $1.2.0$ [22] library, we employ in the current study logistic regression (LR) with a liblinear solver; linear discriminant analysis (LDA) using least-squares solver; linear kernel support vector machine (linearSVM) with squared hinge loss, and $l2-$penalty; random forest classifier (RFC) with a maximum number of trees in the forest set to 400; deep fully connected neural network (DFNN) with six layers of $4, 64, 128, 256, 32, 8$ rectified linear units (ReLU) units; two softmax output units; early stopping; adaptive learning rate; and an ADAM optimizer.

III. RESULTS

The results of TDA application to multichannel EEG time series we summarized for the persistent homology in Figure 1, the number of cycles in Figure 2, and normalized persistence entropy in Figure 3. All chosen TDA features resulted in statistically significantly differing distributions $(p_r \ll 0.05)$, as evaluated with a Wilcoxon rank sums test for healthy cognitive aging versus MCI participants. The above TDA application results allowed for a subsequent supervised clustering with UMAP, as depicted in Figure 4, with clearly separable clusters of healthy cognitive aging versus MCI, with only small overlaps. Finally, the LOOSCV application of the current subject group of 33, allowed us to simulate the real-world point-of-care scenario, in which an unknown condition subject's EEG tested against a machine learning model trained on a limited number of known-label-patients resulted in very encouraging results we summarized in Figure 5. We achieved the highest LOOSCV median results, above 90%, with the linearSVM and DFNN machine learning models.

IV. CONCLUSIONS

We reported a project in which the TDA feature drawn from multichannel EEG wearable recordings in simple short-term memory cognitive tasks allowed for discrimination with a statistical significance of healthy cognitive aging versus MCI elderly participants, as summarized in Figures 1, 2, and 3. A subsequent application of supervised UMAP clustering (see Figure 4) and several shallow, as well as deep learning models (as summarized in Figure 5) further confirmed a possibility for near future point-of-care and home-based diagnostics based on a classification discriminating healthy cognitive aging versus MCI with median accuracies above 90% for the best linearSVM and DFNN models.

We recognize the inherent limitation of the current approach as we only replicate, at this stage, the human-error-

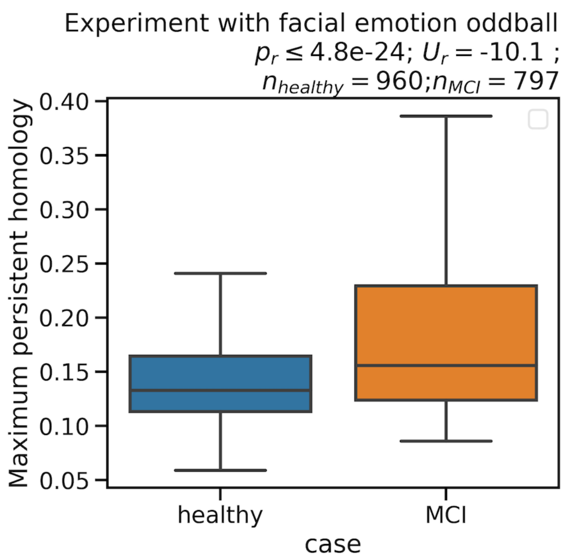

Fig. 1. Persistent homology features [14] of the analyzed EEG with TDA approach from healthy cognitive aging versus MCI participants. Each experimental subject contributed 53 EEG responses on average.

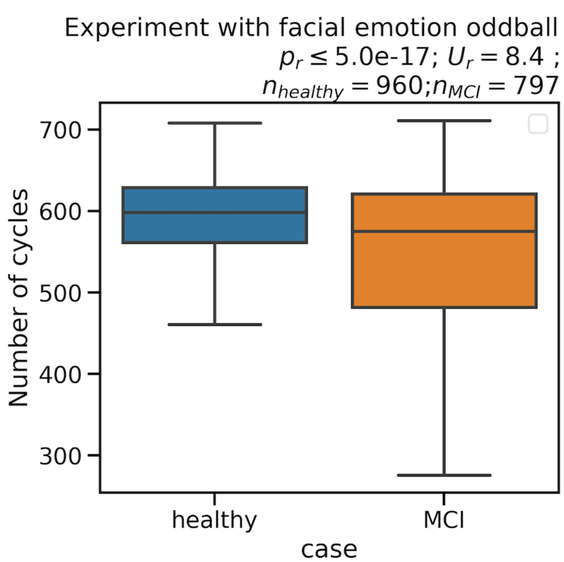

Fig. 2. The number of cycle features [14] of the analyzed EEG with TDA approach from healthy cognitive aging versus MCI participants. Each experimental subject contributed 53 EEG responses on average.

prone subjective paper and pencil test cognitive evaluation criteria converted to binary MCI (MoCA $\leq$ 25), versus healthy cognitive aging (MoCA $>$ 25), which are only subjective estimators of an early onset dementia detection. Furthermore, the present study comprised a limited sample of the elderly, an added restraint of the machine model results. Our next research goal shall be an extension of the current objective neurobiomarker approach, perhaps beyond EEG, including fNIRS and eye-tracking modalities, to further validate the potential of creating true-to-life point-of-

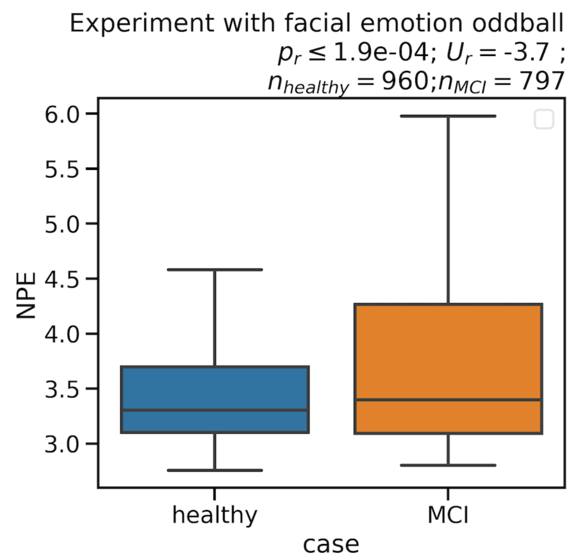

Fig. 3. Normalized persistence entropy features [14] of the analyzed EEG with TDA approach from healthy cognitive aging versus MCI participants. Each experimental subject contributed 53 EEG responses on average.

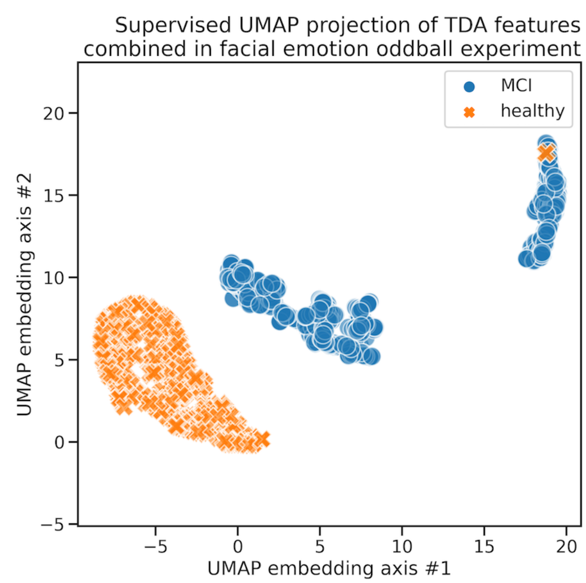

Fig. 4. UMAP supervised clustering results present a possibility to separate healthy cognitive aging versus MCI participant EEG features drawn from the topological data analysis approach.

care standards without the necessity to refer to paper-and-pencil questionings in near future application to home-based dementia early onset monitoring.

Author Contributions

TMR: Originated the idea of the emotional facial expressions oddball experimentation, an application of topological data analysis in application to EEG time-series, and MCI detection using machine learning methods; MOM and MSA helped with recruitment and oversight of elderly participants;

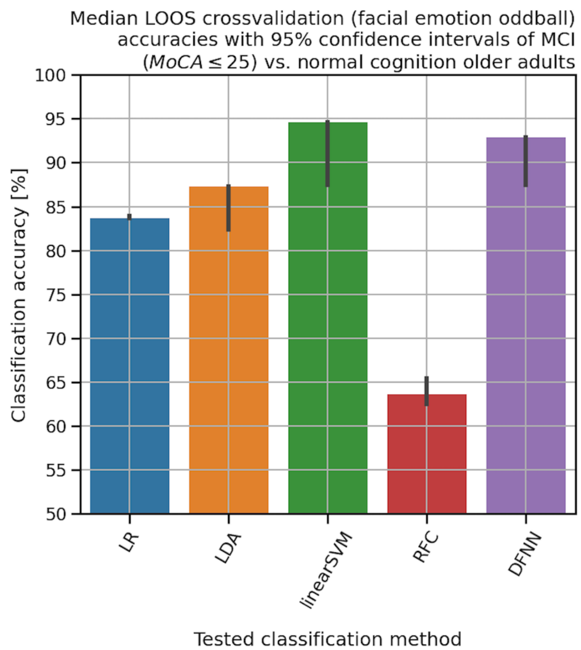

Fig. 5. Classification results using LOOSCV and shallow (LR, LDA, linearSVM, RFC) and deep (DFNN) machine learning models. The chance level was 50%, and all classifiers achieved significantly above it.

TMR coded the EEG examination and machine learning protocols; TMR, MSA, HS, and MOM examined and interpreted outcomes; TMR: wrote the article.

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REFERENCES

[1] WHO, "Risk reduction of cognitive decline and dementia: WHO guidelines," tech. rep., World Health Organization, 2019.

[2] G. Livingston, J. Huntley, A. Sommerlad, D. Ames, C. Ballard, S. Banerjee, C. Brayne, A. Burns, J. Cohen-Mansfield, C. Cooper, S. G. Costafreda, A. Dias, N. Fox, L. N. Gitlin, R. Howard, H. C. Kales, M. Kivimäki, E. B. Larson, A. Ogunniyi, V. Orgeta, K. Ritchie, K. Rockwood, E. L. Sampson, Q. Samus, L. S. Schneider, G. Selbæk, L. Teri, and N. Mukadam, "Dementia prevention, intervention, and care: 2020 report of the Lancet Commission," *Lancet*, vol. 0, jul 2020.

[3] R. C. Petersen, G. E. Smith, S. C. Waring, R. J. Ivnik, E. G. Tangalos, and E. Kokmen, "Mild cognitive impairment: clinical characterization and outcome," *Archives of neurology*, vol. 56, no. 3, pp. 303–308, 1999.

[4] S. A. Sikkes, Y. Tang, R. J. Jutten, and et al., "Toward a theory-based specification of non-pharmacological treatments in aging and dementia: Focused reviews and methodological recommendations," *Alzheimer's Dement.*, no. May, pp. 1–16, 2020.

[5] A. Barachant, D. Morrison, H. Banville, J. Kowaleski, U. Shaked, S. Chevallier, and J. J. T. Tresols, "muse-lsl." ZENODO, May 2019.

[6] T. M. Rutkowski, M. S. Abe, M. Koculak, and M. Otake-Matsuura, "Classifying mild cognitive impairment from behavioral responses in emotional arousal and valence evaluation task – AI approach for early dementia biomarker in aging societies –," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC)*, pp. 5537–5543, 2020.

[7] T. M. Rutkowski, M. S. Abe, T. Komendzinski, and M. Otake-Matsuura, "Older adult mild cognitive impairment prediction from multiscale entropy EEG patterns in reminiscent interior image working memory paradigm," in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC)*, pp. 6345–6348, 2021.

[8] T. M. Rutkowski, M. S. Abe, and M. Otake-Matsuura, "Neurotechnology and AI approach for early dementia onset biomarker from EEG in emotional stimulus evaluation task," in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC)*, pp. 6675–6678, 2021.

[9] T. M. Rutkowski, M. S. Abe, S. Tokunaga, T. Komendzinski, and M. Otake-Matsuura, "Dementia digital neuro-biomarker study from theta-band eeg fluctuation analysis in facial and emotional identification short-term memory oddball paradigm," in *2022 44th Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC)*, (Glasgow, UK), pp. 4129–4132, IEEE Press, July 11-15, 2022.

[10] T. M. Rutkowski, M. S. Abe, S. Tokunaga, H. Sugimoto, T. Komendziński, and M. Otake-Matsuura, "Passive BCI oddball paradigm for dementia digital neuro-biomarker elucidation from attended and inhibited ERPs utilizing information geometry classification approaches," in *2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 2657–2662, IEEE Press, 2022.

[11] T. M. Rutkowski, S. Narebski, P. Bekier, T. Komendzinski, H. Sugimoto, and M. Otake-Matsuura, "Cross-cultural evaluation of dementia passive bci neuro-biomarker candidates," in *2022 Joint 12th International Conference on Soft Computing and Intelligent Systems and 23rd International Symposium on Advanced Intelligent Systems (SCISISIS)*, pp. 1–5, 2022.

[12] T. M. Rutkowski, T. Toshihisa, A. Cichocki, and D. P. Mandic, "Clustering EMD components for muscular interference separation from EEG - a time/frequency approach with different distance measures," in *Proceedings of 23rd SIP Symposium*, (Kanazawa), pp. 52–57, IEICE, November 12–14, 2008.

[13] T. M. Rutkowski and H. Mori, "Tactile and bone-conduction auditory brain computer interface for vision and hearing impaired users," *Journal of Neuroscience Methods*, vol. 244, pp. 45 – 51, 2015.

[14] T. F. Varley, V. Denny, O. Sporns, and A. Patania, "Topological analysis of differential effects of ketamine and propofol anaesthesia on brain dynamics," *Royal Society open science*, vol. 8, no. 6, p. 201971, 2021.

[15] S. Baron-Cohen, *Mind Reading - The Interactive Guide to Emotions*. London, UK: Jessica Kingsley Publishers, 2004.

[16] Y. Fujiwara, H. Suzuki, M. Yasunaga, M. Sugiyama, M. Ijuin, N. Sakuma, H. Inagaki, H. Iwasa, C. Ura, N. Yatomi, *et al.*, "Brief screening tool for mild cognitive impairment in older japanese: validation of the Japanese version of the Montreal Cognitive Assessment," *Geriatrics & gerontology international*, vol. 10, no. 3, pp. 225–232, 2010.

[17] D. Laszuk, "Python implementation of empirical mode decomposition algorithm." https://github.com/laszukdawid/PyEMD, 2017.

[18] A. Patania, G. Petri, and F. Vaccarino, "The shape of collaborations," *EPJ Data Science*, vol. 6, pp. 1–16, 2017.

[19] G. Carlsson, "Topology and data," *Bulletin of the American Mathematical Society*, vol. 46, no. 2, pp. 255–308, 2009.

[20] J. A. Perea, "Topological time series analysis," 2018.

[21] L. McInnes, J. Healy, and J. Melville, "UMAP: uniform manifold approximation and projection for dimension reduction," *arXiv preprint arXiv:1802.03426*, 2018.

[22] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.