Label Distribution Learning for Memory Decline: A Deep Learning Approach Using EEG Analysis

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***Abstract*— Electroencephalogram (EEG) is a potent means for assessing cognitive capabilities, thus suitable for monitoring cognitive interventions, and potentially complementing diagnostic approaches in dementia among the elderly. In this paper, we introduce a novel framework using severity indicator and expectation regression approach to predict memory decline, employing a dynamic graph convolutional neural network (DGCNN) and label distribution learning (LDL). The framework is applied to the open dataset Mind-Brain-Body (LEMON) from the Max Planck Institute Leipzig. Our initial findings suggest that EEG measurements can effectively supplement traditional psychometric tools in assessing memory loss and cognitive decline.**

***Clinical Relevance*— This framework positions EEG measurements as an adjunct to bolster existing psychometric assessments for memory loss and cognitive decline.**

I. Introduction

Ageing population in society poses risk of high dementia prevalence, prompting the need for self-management approaches for evaluation methods, and personalized interventions among the elderly. The increasing portability and affordability of off-the-shelf EEG devices show great promise as a modality for measuring cognitive impairments associated with early stages of dementia, which are otherwise executed with psychometric tools in clinical settings. One such tool is the California Verbal Learning Task (CVLT) is a widely used psychometric tool and is a sensitive measure of episodic memory, available in the LEMON [1] dataset for 228 participants.

II. Methods

Fig. 1 shows the proposed model workflow. EEG data used are resting state, eyes closed EEG signals, which were then down sampled and filtered to all 62 EEG channels. The adjacency matrix for graph representation consists of band differential entropy for features and spatial relationships between EEG channel for nodes. DGCNN model [2] was used to dynamically learn the intrinsic relationship. Memory general scale was reduced into principal component based on standardized CVLT measurement criteria, then a gaussian function was applied to generate LDL input label distribution. The output layer is also treated as a label distribution, with the input distribution using Kullback-Leibler (KL) divergence as loss to optimize the model.

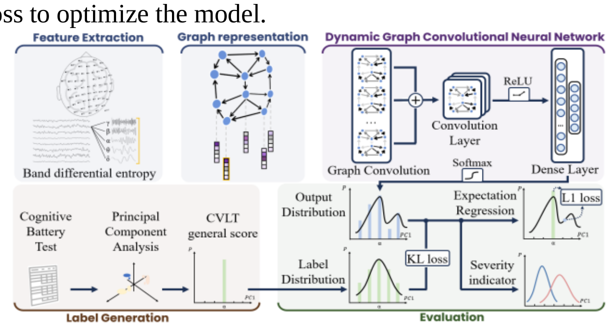

Figure 1. The instruction pipeline of the proposed model.

III. Results

Comparing regression for model performance and assessing the classification accuracy for diagnosing memory decline are used to evaluate three label distribution conversion metrics in Table I. Regression employed correlation coefficient (CC) and Root Mean Square Error (RMSE) are used to evaluate the model performance. Classification performance of the severity indicator uses a Force Choice Recognition (FCR) cutoff [3] to categorize controls, evaluated with sensitivity, specificity, F1-score, and Area Under the Curve (AUC).

TABLE I. Comparison of Regression and Severity Indicator

Conversion metrics	Regression		Severity Classification			
	CC	*RMSE*	*SENS*	*SPEC*	*F1*	*AUC*
Expected value	**.499**	**.094**	.603	**.798**	**.624**	**.71**
Maximum value	.430	.156	.616	.739	.604	**.71**
Upper range	.399	**.094**	**.712**	.513	.568	.67

IV. Discussion & Conclusion

This paper proposes a novel framework for predicting memory decline in dementia detection using a DGCNN with LDL for a severity indicator and expectation regression. Machine learning experiments on the LEMON dataset achieved moderate accuracy: 0.499 CC and 0.094 RMSE for label distribution expectation regression, and 0.624 F1-score and 0.71 AUC for severity classification. Sample heterogeneity and lack of standardized clinical examinations might be contributing factors to the model's shortcomings. Future work will evaluate the model with a simpler EEG device and explore broader dementia indicators beyond memory.

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