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

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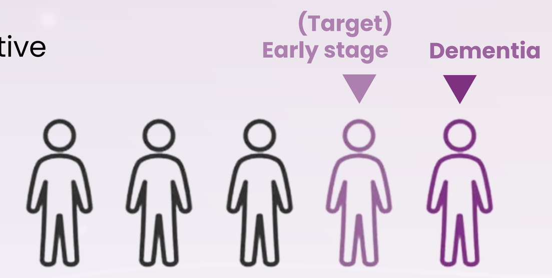
46TH ANNUAL International Conference of the IEEE Engineering in Medicine and Biology Society, Orlando 2024, July 15-19, 2024

Poster No. D5P-37-011

INTRODUCTION

- **Challenge:** Increased dementia prevalence due to aging population necessitates better evaluation methods and interventions for elderly.
- **Electroencephalogram (EEG) Potential:** Offers a promising, portable, and affordable way to assess cognitive decline compared to traditional psychometric tools.
- **Novel Approach:** This framework proposes Dynamic Graph Convolutional Neural Network (DGCNN), Label Distribution Learning (LDL) on EEG measurements data to estimate memory decline.
- **Initial Results:** EEG has the potential to complement psychometric tools for assessing memory loss.
- **Clinical relevance:** This framework could enhance early detection and potentially aid in dementia diagnosis.

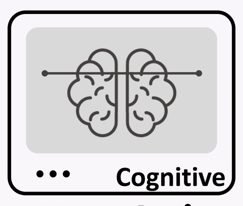


In Japan, about one in five elderly people aged 65 and over is expected to develop dementia.

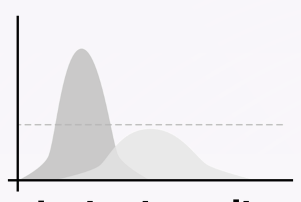
OBJECTIVES

This study aims to develop an AI driven EEG framework using DGCNN and LDL to predict memory decline and potentially complement dementia diagnostics in elderly population.

EEG capture
EEG dataset for cognitive detection collected with non-invasive devices.

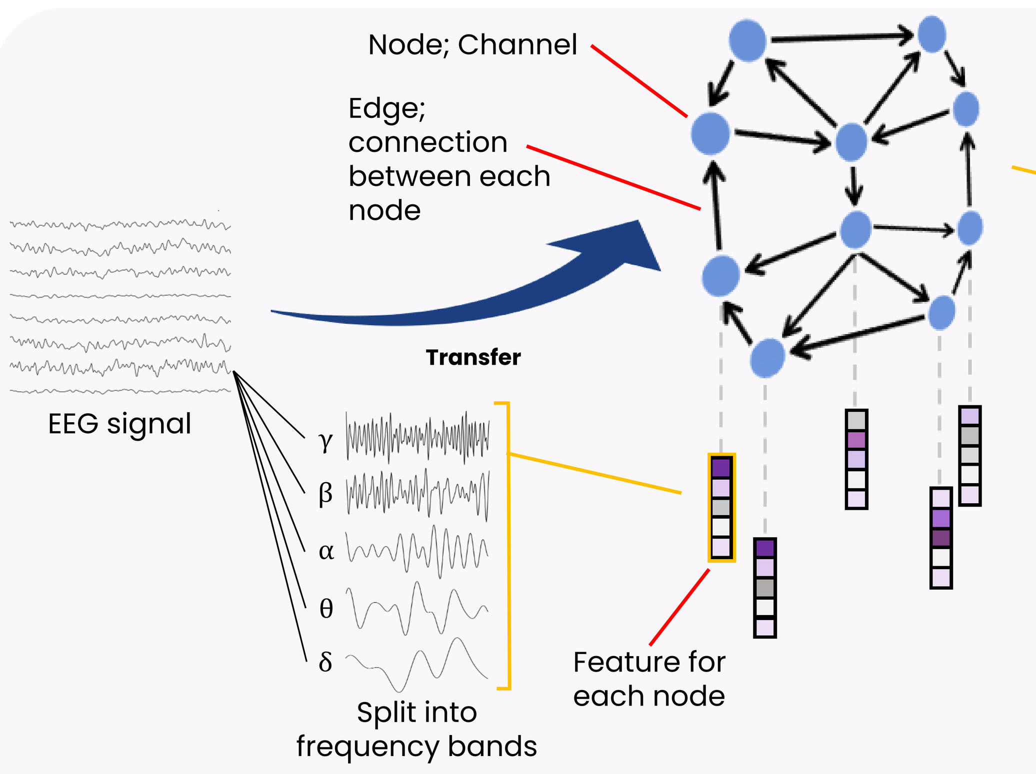


AI analysis
Employ advanced machine learning techniques to analyze EEG patterns and predict cognitive decline.



Instant result
Generate real-time feedback on memory function, potentially aiding early detection for dementia.

FEATURE AND GRAPH REPRESENTATION



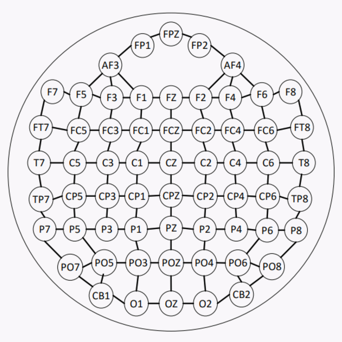


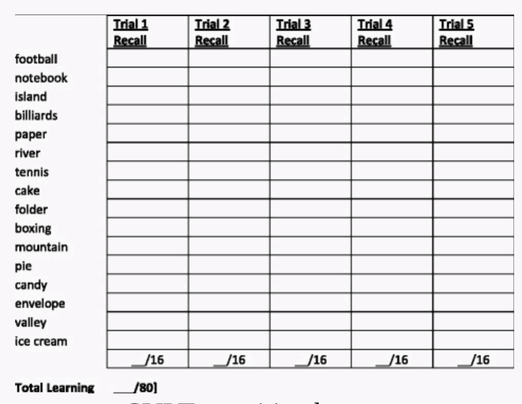
Illustration of the connections among the 62 EEG channels [1]

The weights of the adjacency matrix is computed as follows:

$$w_{ij} = \begin{cases} \exp\left(-\frac{[dist(i,j)]^2}{2\theta^2}\right), & \text{if } dist(i,j) \le \tau \\ 0, & \text{otherwise} \end{cases}$$

- **Data selection:** Resting state, eyes closed, rest-state EEG signals from Max Planck Institute Leipzig Mind-Brain-Body open dataset (LEMON) [2].
- **Preprocessing:** The data was down sampled to 100 Hz and filtered
- **Feature extraction:** Band differential entropy was calculated for each channel.
- **Adjacency matrix:** A fully connected adjacency matrix was created, indicating that all channels are considered to be connected.

LABEL DISTRIBUTION LEARNING



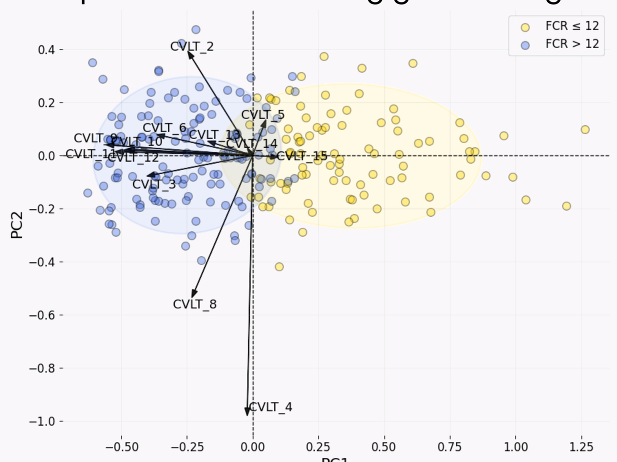
CVLT cognitive battery test

CVLT (California Verbal Learning Task)

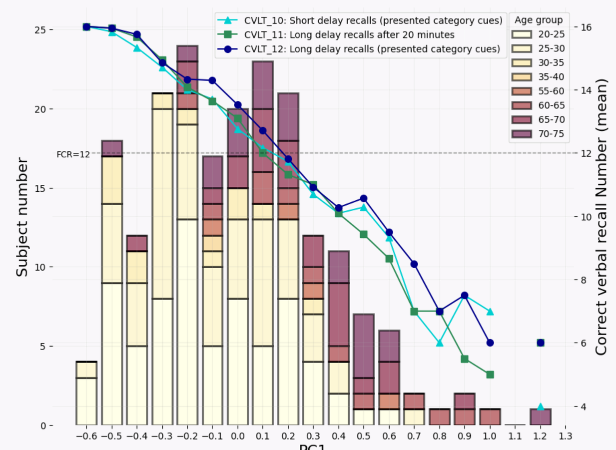
- The task tests memory over time. Subjects learn a 16-word list repeated five times, then encounter another list potentially interfering with their memory.
- After immediate recall and categorization of the first list, subjects perform various tasks (unspecified).
- A delayed free recall test occurs after 20 minutes, where they again recall and categorize words from the first list.
- Finally, recognition memory is assessed by presenting a new list and asking subjects to identify words from the original 16.

PCA (Principal Component Analysis)

PCA scores were derived from multiple cognitive battery test measures to create a composite label reflecting general cognitive function.



CVLT biplot of each component and subject scatter plots



Bar graph of PC1 score distribution by subject age and CVLT score line

- **Horizontal axis:** number of words recalled in CVLT short time delay, long time delay, and overall word count
- **Vertical axis:** susceptibility of subjects to interference

- Subjects' overall CVLT scores show an effect trend.
- Forced Choice Recognition (FCR) cutoff demonstrated high specificity in the performance validity testing (PVT)

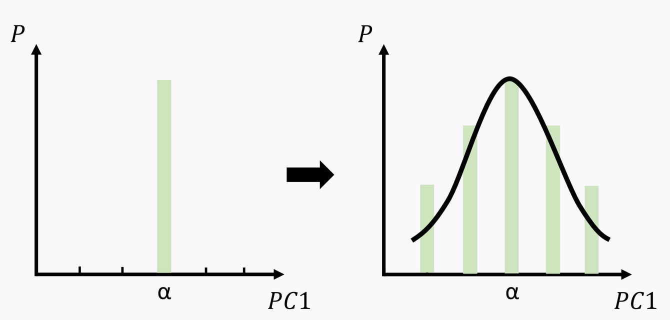
- CVLT_4= Proactive Interference (interference from previously learned information) −4～4
- CVLT_9= number of correct recalls (short delay) 0～16
- CVLT_10 = number of correct recalls when category cues are presented (short delay) 0～16
- CVLT_11 = number of correct recalls after 20 minutes (long delay recall) 0～16
- CVLT_12 = number of correct recalls when category cues are presented (long delay recall) 0～16

LDL (Label Distribution Learning)

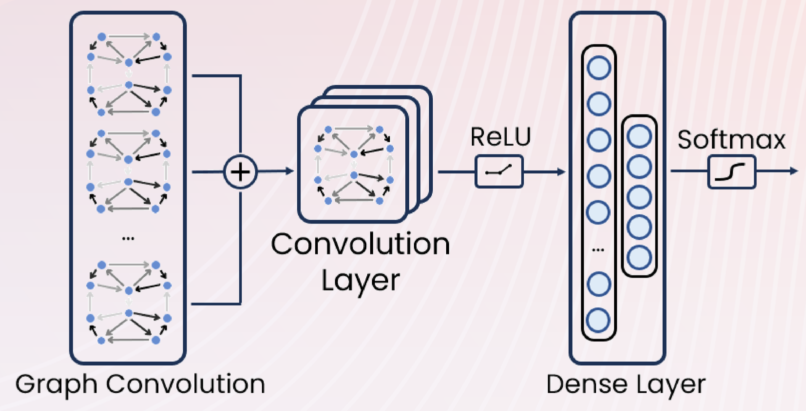
LDL assigns to an instance a distribution over a set of labels rather than a single label or multiple labels, allowing us to obtain useful information to improve model performance

$$p(l_i|\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(l_i-\mu)^2}{2\sigma^2}\right)$$

The probability density function of the normal distribution is used to generate the grand-truth distribution p.



Dynamic Graph Convolutional Neural Network



Dynamic Graph Convolution: Learns how EEG channels interact during tasks, adapting to changing patterns.
Convolution & Activation: Extracts and refines meaningful features from EEG signals, introducing non-linearity for complex pattern recognition.
Dense & Softmax Layers: Combines features and predicts the probability of cognitive decline.
5-Fold Cross-Validation: Rigorous testing ensures model accuracy and reliability on unseen data.

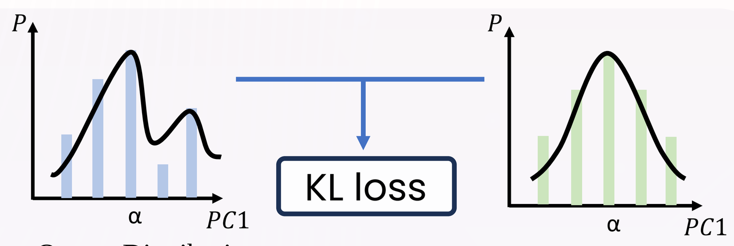
Key Advantages

Captures Spatial Relationships: The graph structure effectively represents the spatial connections between different brain regions, allowing the model to learn how these regions interact.
Dynamic Learning: The ability to adapt the graph connections during training enables the model to capture the dynamic nature of brain activity.
Feature Extraction: The combination of graph convolution and traditional convolution layers allows for effective feature extraction from EEG data.

Loss function

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.

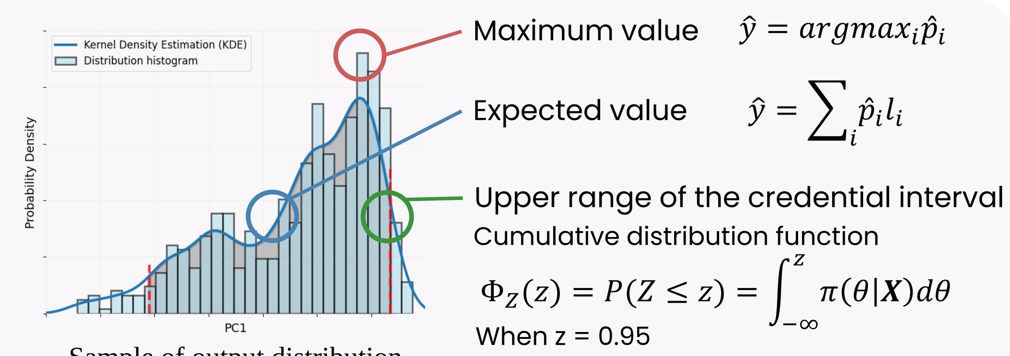
$$L_{KL} = \sum_i p_i \ln\frac{p_i}{\hat{p}_i}$$



Output Distribution   Label Distribution

RESULT

Regression Analysis: Predicted the severity of memory decline using continuous values.
Classification Analysis: Classified individuals into severity indicator groups for memory decline.
Distribution Conversion Metrics: Assessed model performance by comparing predicted and actual label distributions using three different metrics.



$\hat{y} = argmax_i \hat{p}_i$

$\hat{y} = \sum_i \hat{p}_i l_i$

$\Phi_Z(z) = P(Z \le z) = \int_{-\infty}^{z} \pi(\theta|X)d\theta$

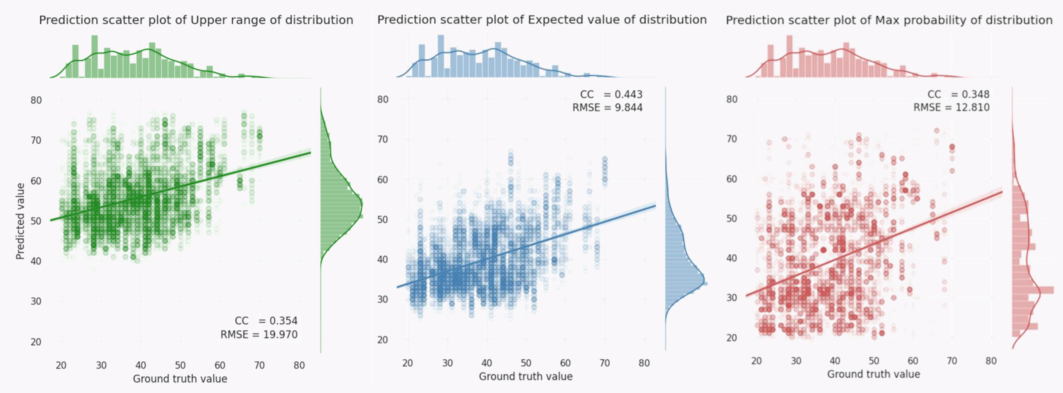
Sample of output distribution

Regression

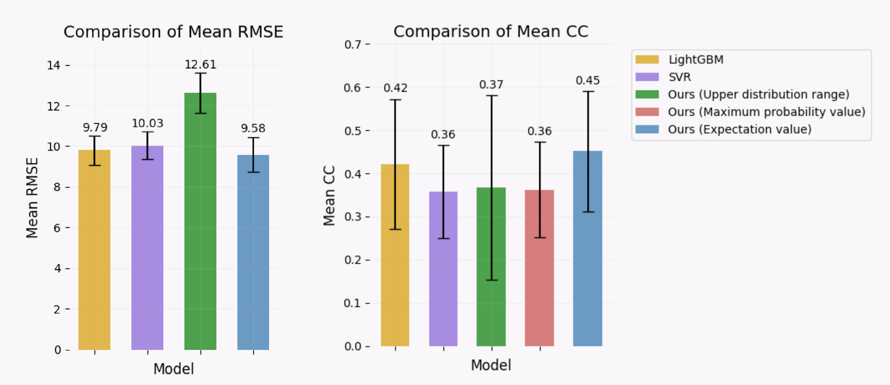
Evaluation metrics:
- Correlation Coefficient (CC)
- Root Mean Square Error (RMSE)

between the ground-truth and expected memory scores.

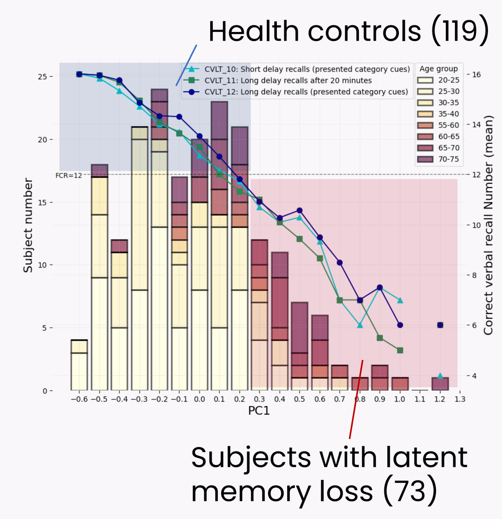
Model evaluation on expected value of distribution achieving the best CC of 0.443 and RMSE of 9.844.



Model comparison:
- LightGBM: A gradient boosting framework that uses tree-based learning algorithms.
- Support Vector Regression (SVR): A regression algorithm that uses a hyperplane to predict continuous values.
- LDL-DGCNN (Our models): This comparison aimed to assess the strengths and weaknesses of each model in predicting memory decline.



Classification



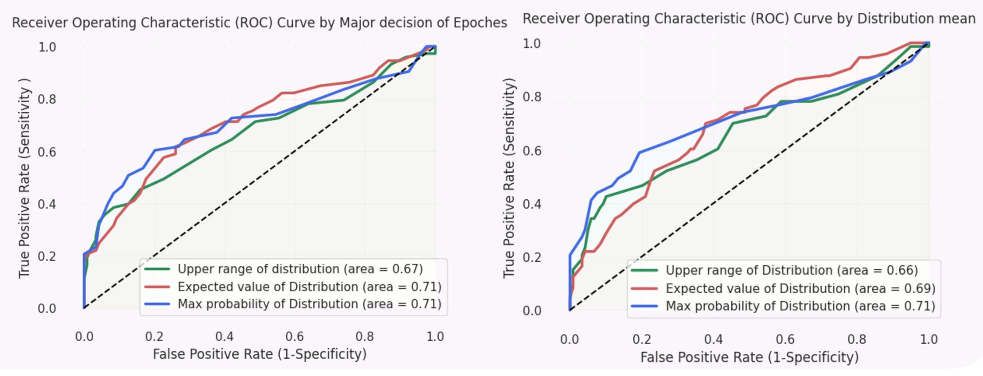
		Ground truth	
		Positive	Negative
Predict	Positive	44	24
	Negative	29	95

Classification model result

Severity Indicator:
Utilized the Force Choice Recognition (FCR) cutoff [3] to categorize individuals as controls or potential memory decline cases.

Performance Metrics:
Sensitivity, Specificity, F1-Score, Area Under the Curve (AUC)

The model demonstrated promising performance in classifying dementia severity, achieving an F1-score of 0.624 and an AUC of 0.71, suggesting potential for further development and refinement for clinical application.



CONCLUSION

- **Novel Framework:** This paper introduced a new framework for predicting memory decline using DGCNN with LDL, demonstrating its potential for dementia detection.
- **Moderate Accuracy:** The model achieved moderate accuracy on the LEMON dataset, indicating the potential of EEG-based approaches for early detection.
- **Limitations:** Sample heterogeneity and lack of standardized clinical data may have impacted the model's performance.
- **Future Directions:** Further research will focus on evaluating the framework with simpler EEG devices and exploring additional dementia indicators. This could lead to more accessible and comprehensive tools for early dementia detection and intervention.

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ACKNOWLEDGMENT

This research is made possible by Macnica and neurotechnology R&D initiatives. Acknowledgment also goes to Dr. Toshihisa Tanaka of Tokyo University of Agriculture and Technology for the rendered technical advice.

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