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Low-Rank Tensor Networks with Inter- and Intra-Modality Consistency Regularization for Psychological Resilience Prediction

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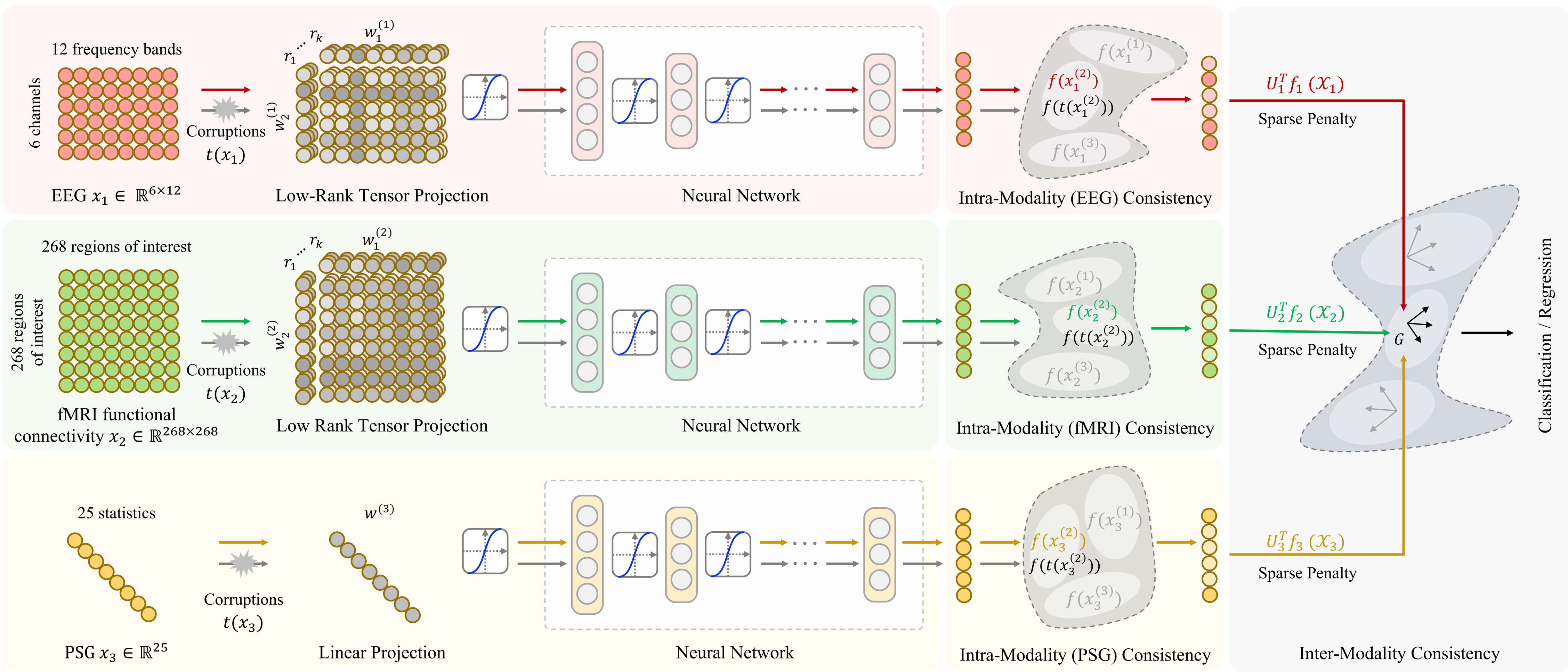
Background of Psychological Resilience Prediction

IMPACT Psychological resilience is a dynamic process where protective resources interact with stress to minimize negative effects. It is essential for mental well-being and coping strategies. It is essential to identify individuals at risk of psychological problems and intervene proactively to prevent tragic outcomes.

PROBLEM Recent studies have made progress in constructing prediction models of psychological resilience relying on data reduction via handcrafted summarization of data statistics or feature selection algorithms, while deep learning algorithms suffer from data scarcity.

Proposed Method for Resilience Prediction



FRAMEWORK Fig. 1 The proposed Inter- and Intra-modality Consistency Regularized Low-rank Tensor Networks (IICR-LTN) contains three core designs.

Low-rank Tensor Networks are designed models constraining the weight parameters in the network to have a low intrinsic rank, simplifying the network model with reduced parameters and capturing elementary features.

Inter-modality Consistency Regularization regularizes the model to learn a representation that explains features from multiple modalities and penalizes redundant features.

Intra-modality Consistency Regularization introduces augmented samples via masking-based corruptions and enforces the invariant representation across corruptions of original samples, making the model less noise-sensitive.

Experimental Results on Different Datasets

Table 2 Comparative experiments on predictive analysis of Connor-Davidson Resilience Scale (CD-RISC) using EEG, fMRI, and PSG signals with unsupervised feature selection methods, Canonical Correlation Analysis (CCA) methods, and our proposed method as feature extraction techniques. Accuracy (Acc.) and F1 score are reported for binary classification. Mean absolute error (MAE) and r^2 are reported for regression.

Method		Acc. (train)↑	Acc. (test) ↑	F1 (train) ↑	F1 (test) ↑	MAE (train) ↓	MAE (test) ↓	r^2 (train) ↑	r^2 (test) ↑
Feature Selection	LAP [20]	0.8136	0.6000	0.7168	0.3571	4.9584	5.2184	0.0201	<0
	SPEC [21]	0.9333	0.6222	0.9189	0.5143	4.9919	5.2266	0.0068	<0
	MCFS [22]	**0.9556**	0.6444	**0.9474**	0.5556	4.9584	5.2184	0.0201	<0
CCA	GRCCA [23]	0.8232	0.6000	0.7504	0.5000	3.6279	4.7613	0.4169	0.1178
	MCCA [24]	0.8505	0.6000	0.8003	0.4706	4.4492	4.9608	0.1906	<0
	GCCA [25]	0.8854	0.7778	0.8550	0.7222	3.0837	4.5517	0.5896	0.1381
	TCCA [26]	0.7818	0.6889	0.7173	0.6111	4.3680	4.9180	0.2422	0.0227
Proposed		0.8909	**0.8444**	0.8596	**0.8108**	**2.0906**	**3.2493**	**0.6582**	**0.3858**

Table 3 Ablation studies on the modalities for predicting the Connor-Davidson Resilience Scale (CD-RISC) score (or class). The EEG signals, fMRI signals, and PSG signals are respectively ablated while accuracy (Acc.) and F1 score are reported for binary classification. Mean absolute error (MAE) and r^2 are reported for regression.

Modalities			Acc. (train)↑	Acc. (test) ↑	F1 (train) ↑	F1 (test) ↑	MAE (train) ↓	MAE (test) ↓	r^2 (train) ↑	r^2 (test) ↑
EEG	fMRI	PSG								
×	✓	✓	0.8879	0.6889	0.8560	0.5625	3.4010	3.9998	0.4614	0.2851
✓	×	✓	**0.9172**	0.7778	**0.8967**	0.7059	3.1732	4.0303	0.5253	0.2995
✓	✓	×	0.7657	0.6000	0.6839	0.4375	3.3362	4.0052	0.4679	0.2862
✓	✓	✓	0.8909	**0.8444**	0.8596	**0.8108**	**2.0906**	**3.2493**	**0.6582**	**0.3858**

Methods Acc. (%)	SEED		SEED-IV	
	Mean	Std	Mean	Std
Concatenation [13,14]	83.7	-	73.7	8.9
Max [13]	81.7	-	73.2	9.3
Fuzzy Integral [13]	87.6	19.9	73.2	8.7
DGCNN [15]	90.4	8.5	-	-
SLFN [16]	91.5	-	-	-
Bimodal-LSTM [17]	94.0	7	-	-
BDAE [14,18]	91.0	8.9	79.7	**4.8**
DCCA-AM [19]	94.6	6.2	85.3	5.6
Proposed	**97.6**	**4.9**	**88.4**	5.6

Table 1 Performance comparison of the proposed method with state-of-the-art approaches on two public multimodal emotion recognition datasets. The experiments are conducted using EEG signals and eye movements to classify three emotions on the SEED dataset and five emotions on the SEED-V dataset. The mean and standard deviation (Std) of accuracy are reported, with the best performances highlighted by bold.

Comparative Experiments show IICR-LTN performs better than existing work with all designs.

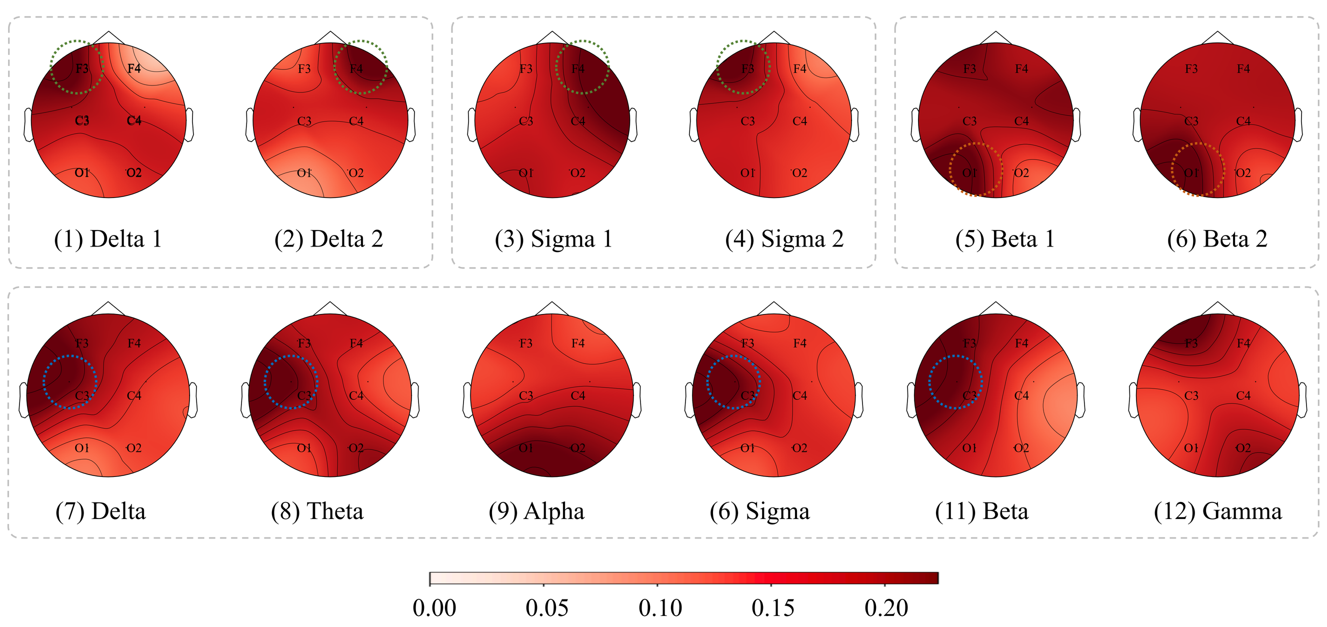


Fig. 2 The topographic maps of absolute weight distribution on electrodes and frequency sub-bands of EEG signals. Darker colors indicate higher absolute weights, while lighter colors indicate the opposite.

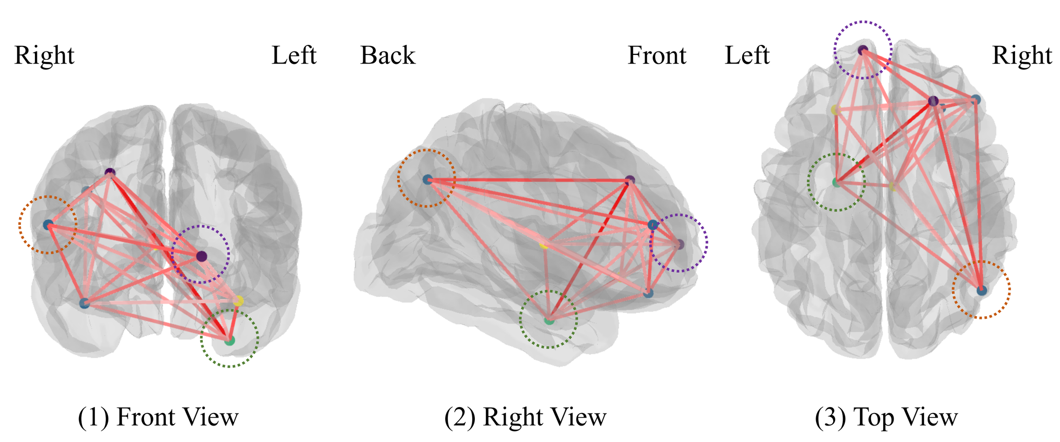


Fig. 3 The learned weights on functional connectivities of fMRI. Functional connectivities between regions of interest are marked by lines, with darker red indicating larger absolute values of weights while lighter colors indicate the opposite.

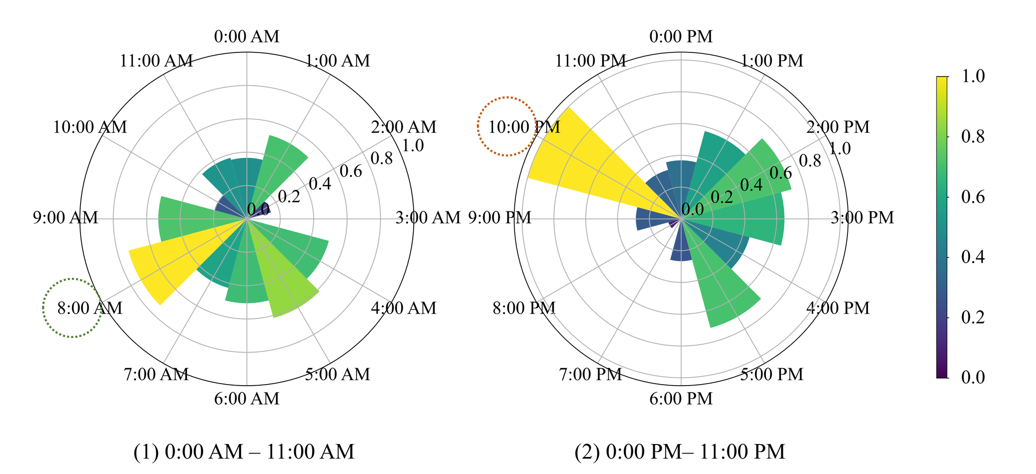


Fig. 4 Absolute weights learned on PSG activities from 0-11 hours AM and 0-11 hours PM. Taller bars represent higher absolute weights.

Interpretability Experiments are conducted to provide further insight.

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