Does Complexity Pay Off? Applying Advanced Algorithms to Depression Detection on the GLOBEM Dataset

Sebastian Cavada, Yevheniia Kryklyvets, Alvaro Cabrera

MBZUAI

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Presenter resume

Sebastian Cavada received his bachelor's degree in Computer Science in 2023 from the Free University of Bolzano, Italy. He is currently a master's student specializing in Computer Vision at MBZUAI, Abu Dhabi. His research interests span the application of AI for societal wellbeing, with a focus on health, and advanced 3D reconstruction techniques.

Aim and Contribution of the paper

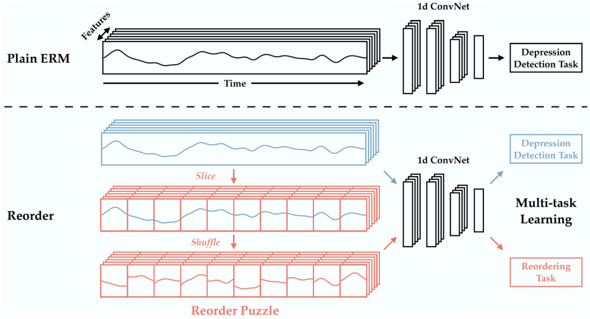
1. Extending the GLOBEM platform with 4 different families of SOTA algorithms in multivariate time-series prediction
   1. TSMixer Chen et al. (2023) (All-MLP) to test how ALL-MLP generalizes
   2. CrossFormer Zhang and Yan (2023) (Transformer based) to Study how mixing the features and time dimensions perform
   3. CNN+LSTM Widiputra et al. (2021) (Recurrent-based network) to Study the impact of memory on the overall performances
   4. GRU Chung et al. (2014) (Gated recurrent unit) analyzes the effect of reduced parameter complexity while retaining memory capabilities
2. Introduce a novel algorithm to improve on the original best-performing model
3. In-depth analysis of the adapted algorithms and their performance on the GLOBEM dataset

GLOBEM Datasets, Xu et al. (2023)

Table 1: Comparison of Related Sensor-based Human Behavior Datasets and Research Studies

	GLOBEM Dataset	**StudentLife** [4]	**CrossCheck** [12]	**En-Gage** [41]	**Related Research** [20, 97, 101]	**Other Human Behavior Datasets WOODS** [37]
# of Subjects	705 (497 unique)	48	34	29	<400	9
Time Scale	3 months $\times$ 4 years	10 weeks	2 years	4 weeks	Months	Hours $\times$ 36 devices
Open-source	Yes	Yes	Yes	Yes	No	Yes
Domain Generalization	Yes	No	No	No	No	Yes

Reorder algorithm



Experimental results

Full results

Model	Number of Parameters*	Results		
		Single Dataset	Leave one out	Pre/Post Covid
Reorder + CNN-LSTM	32,138	0.629 ± 0.045	0.542 ± 0.009	0.530 ± 0.001
Reorder	**10,162**	**0.626±0.063**	**0.548±0.030**	**0.513±0.009**
CNN-LSTM	**24,378**	**0.601±0.026**	**0.513±0.009**	**0.507±0.004**
GRU	**62,226**	**0.591±0.034**	**0.516±0.011**	**0.502±0.001**
Crossformer	**131,527**	**0.590±0.001**	**0.503±0.003**	**0.516±0.002**
ERM-Transformer	12,354	0.584±0.013	0.509±0.008	0.512±0.016
IRM	2,698	0.573±0.016	0.506±0.006	0.499±0.000
ERM-1dCNN	2,698	0.568±0.006	0.510±0.008	0.514±0.006
ERM-Mixup	2,698	0.568±0.006	0.501±0.008	0.507±0.004
ERM-LSTM	22,186	0.565±0.019	0.512±0.006	0.512±0.003
TSMixer	**43,429**	**0.543±0.035**	**0.521±0.006**	**0.499±0.000**
CSD-D	2,839	0.562±0.022	0.521±0.002	0.512±0.006
Siamese Network	2,664	0.545±0.025	0.509±0.010	0.515±0.002
CSD-P	2,875	0.542±0.010	0.511±0.006	0.516±0.000
ERM-2dCNN	12,994	0.533±0.013	0.510±0.006	0.504±0.006
DANN-D	3,281	0.526±0.016	0.514±0.004	0.514±0.000
MLDG-D	2,698	0.522±0.013	0.511±0.006	0.495±0.004
MLDG-P	2,698	0.508±0.011	0.510±0.003	0.500±0.003
MASF-D	2,970	0.505±0.006	0.505±0.001	0.504±0.007
DANN-P	3,578	0.502±0.002	0.500±0.000	0.500±0.000
MASF-P	2,970	0.495±0.007	0.505±0.004	0.509±0.011

*All results are in descending order, our methods in different colors, results are in balanced accuracy. The standard deviation is calculated on the number of runs between the datasets. * The number of parameters takes into account only trainable parameters - The comma is used to separate thousands, while the point is used for decimals.*

Conclusion and Future Work

Conclusion and Future Work

- Evaluated SOTA algorithms and original deep learning methods for depression detection using wearable data
- Consistently low accuracies across all methods, aligning with Xu et al. (2023)
- Data may **lack sufficiently informative features** for reliable depression detection
- Novel Reorder + CNN_LSTM algorithm showed improvements in one out of three tasks
- Baseline Reorder maintains superior computational **Pareto efficiency** with the best accuracy-to-parameter ratio
- **Increased model complexity did not translate to better performance**

Future Work

- **Enhance Dataset:**
  - Incorporate additional sensor signals such as Heart Rate Variability (HRV) and Saturation of Peripheral Oxygen (SpO2)
  - Utilize more granular measurements like minute-per-minute HRV
- **Explore New Data Types:**
  - Integrate electrocardiogram (ECG) data from devices like the Apple Watch
  - Leverage new sensors as they become available on emerging wearable devices
- **Regularization techniques**
  - Investigate new regularization techniques as they showed promising results with reorder.
- **Broaden Research Scope:**
  - Analyze the impact of adding demographic information as input to enhance domain generalizability
  - Conduct studies on larger and more diverse populations to validate findings

Thank you for your attention!
Any Questions?

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