Combining 3D Image and Tabular Data via the Dynamic Affine Feature Map Transform

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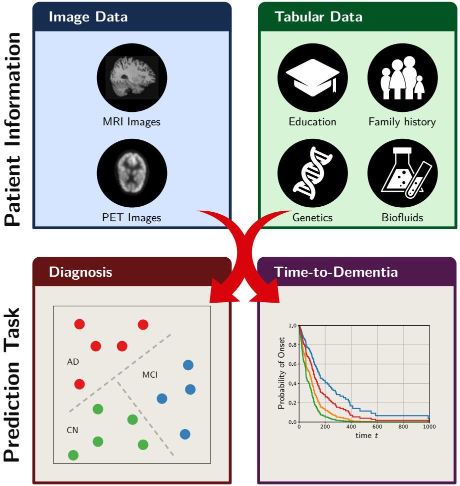
Multi-modal Data in Alzheimer's Disease

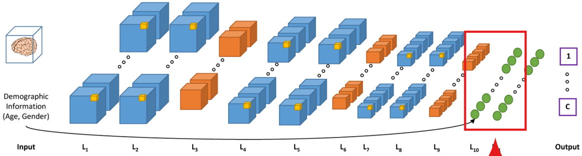


- Data modalities are **diverse**.
- Effective modelling of cognitive decline requires taking a **holistic view**.
- 2 main tasks:
    1. Alzheimer's diagnosis (*classification*),
    2. Prediction of time of dementia onset (*time-to-event analysis*).

Data Integration in CNNs

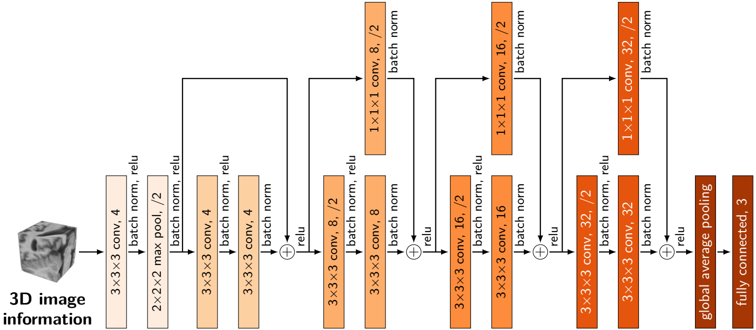
- Deep convolutional neural networks (CNNs) have become and important tool in Alzheimer's disease.
- **Problem:** In current architectures, the interaction between different data types is very limited.
- **Goal:** Enable the CNN to truly view image information in the context of the tabular information, and vice versa.

Esmaeilzadeh et al. (2018):



Concat tabular information with latent image descriptor

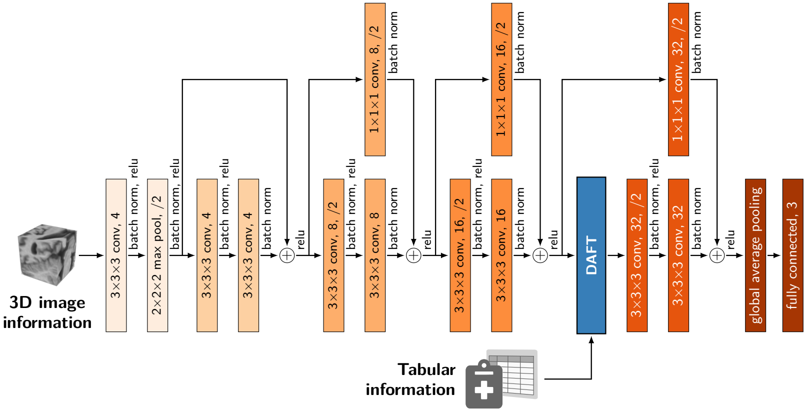
Backbone Architecture



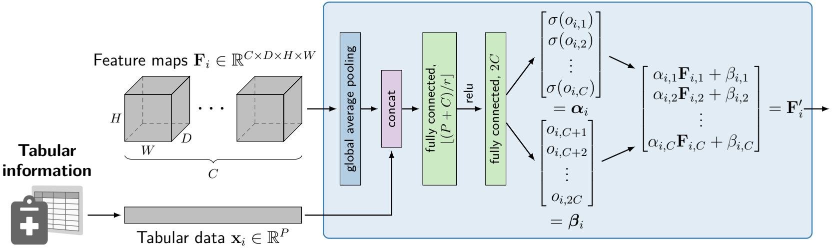
Tabular data often contain high-level information

⇒ use ResNet to extract high-level concepts from the MRI (He et al., 2016).

Proposed Network Architecture



Add *The Dynamic Affine Feature Map Transform* (DAFT) to the last residual block.



- **Idea:** Two-way exchange of information between high-level image concepts and tabular data.
- **Auxiliary neural network** dynamically **incites or represses feature maps** conditional on both image and tabular information.

Experiments

- T1 MRI from the Alzheimer's Disease Neuroimaging Initiative (Jack et al., 2008).
- **Image data**: 64^3 region of interest around left hippocampus.
- **Tabular data**: 9 features (demographics, APOE4, CSF, AV45-PET, FDG-PET).
- 5-fold debiased cross-validation scheme (Wen et al., 2020):
  1. Diagnosis (*classification*).
  2. Time-to-Dementia onset (*see paper*).
- Compare with 8 competing methods.

Experiments – Diagnosis

1341 subjects:

- Dementia (19.6%)
- MCI (40.1%)
- CN (40.3%)

	I	T	Balanced Accuracy ↑ Validation	Testing
Linear Model	✗	L	0.571 ± 0.024	0.552 ± 0.020
ResNet	✓	–	0.568 ± 0.015	0.504 ± 0.016
Linear Model /w ResNet Features	✓	L	0.585 ± 0.050	0.559 ± 0.053
Concat-1FC	✓	L	0.630 ± 0.043	0.587 ± 0.045
Concat-2FC	✓	NL	0.633 ± 0.036	0.576 ± 0.036
1FC-Concat-1FC	✓	NL	0.632 ± 0.020	0.591 ± 0.024
Duanmu et al. (2020)	✓	NL	0.634 ± 0.015	0.578 ± 0.019
FiLM (Perez et al., 2018)	✓	NL	0.652 ± 0.033	0.601 ± 0.036
DAFT	✓	NL	0.642 ± 0.012	**0.622 ± 0.044**

I: Uses images. T: Uses tabular data. L: Linear model. NL: Non-linear model.

Conclusion

- Brain MRI can only capture a facet of the underlying dementia-causing changes.
- Tabular information are important to view the MRI in the right context.
- DAFT learns to incite or repress high-level concepts learned from a 3D image, conditional on both image and tabular information.
- DAFT is a versatile approach to integrating image and tabular data.

Thanks For Your Attention!

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www.ai-med.de

github.com/ai-med

AI_Medic

Lab for AI in Medical Imaging

Founding sources: Bavarian State Ministry of Science and the Arts, Federal Ministry of Education and Research.

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