Multi-Modal Feature-level Integration for Alzheimer's Disease Classification

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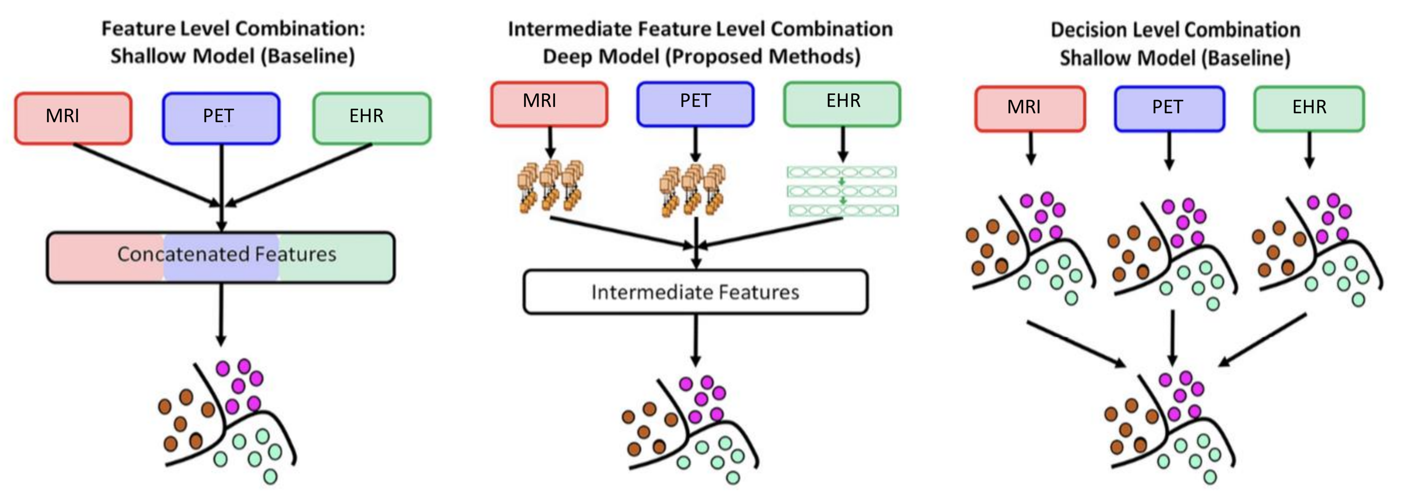
Abstract: Alzheimer's disease is one of the leading causes of dementia. Imaging(MRI, PET), EHR, and genomics are used for patient detection. MRI and PET scans can offer complementary information. Most previous works focus on a smaller subset of these 4 data or manual feature extraction. We propose an end-to-end deep learning framework for combining MRI, PET, and EHR data, removing the need for feature extraction, while also leveraging complementary information of these modalities. Our preliminary results show that training models using joint representation is feasible.

MOTIVATION and PREVIOUS WORK

Alzheimer's disease is the 7th leading cause of death in America in 2020, with 305 billion dollars spent in patient care in America alone. Early detection of Alzheimer's disease can play important role in improving the care of these patients. Imaging modalities, clinical history, and genomics are used to get a diagnosis. Several works in the past have used deep learning-based approaches to make Alzheimer's disease stage predictions.

Authors in [5] used MRI and PET to stage Alzheimer's disease (AD) vs Normal (CN) vs MCI (Mild cognitive impairment). Other works [2] use MRI + EHR data for making these predictions. Authors in [3] extracted the features from imaging modalities and then used ML algorithms to make stage predictions.

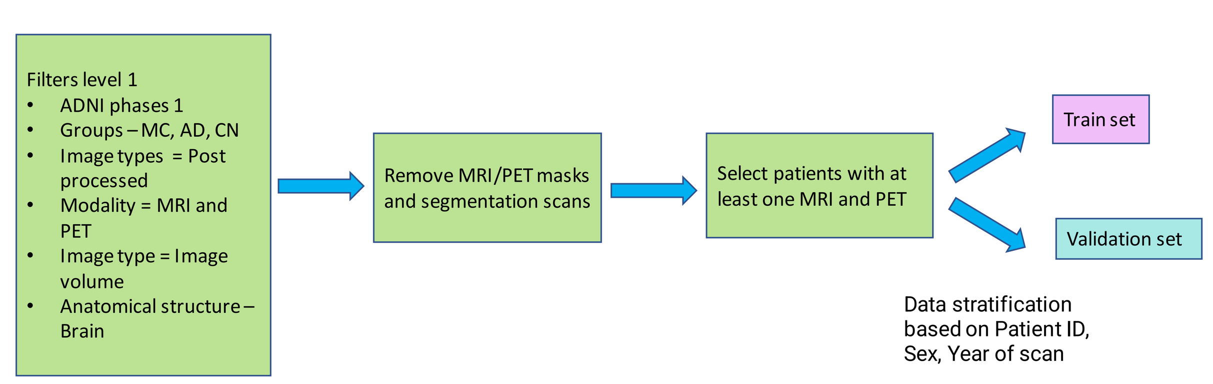


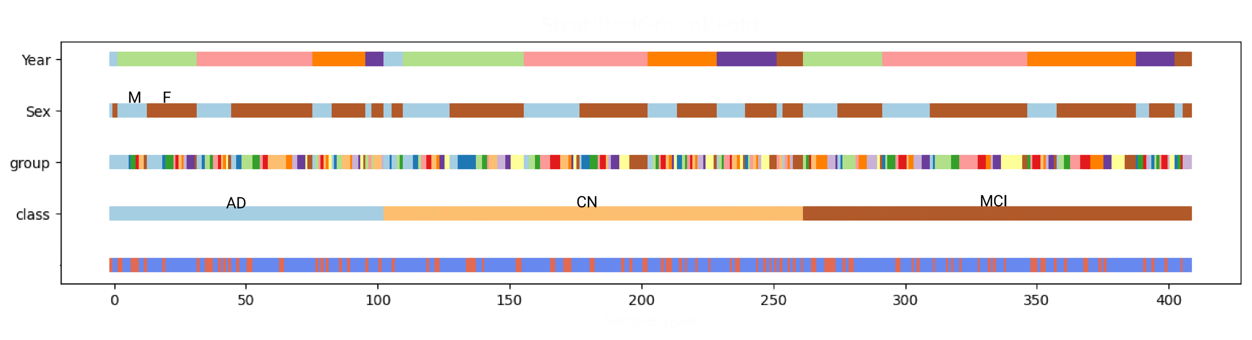
Most previous works used decision-level or intermediate feature-level combinations. In this work, we explore the potential of feature-level combination in combining two imaging modalities (MRI, PET) and one tabular modality (EHR) in Alzheimer's disease staging.

We use autoencoders to learn image representations and then combine that with EHR data before making it through a deep learning network to learn features jointly. This can allow the model to learn complementary information from all the modalities to make the decision.

DATASET

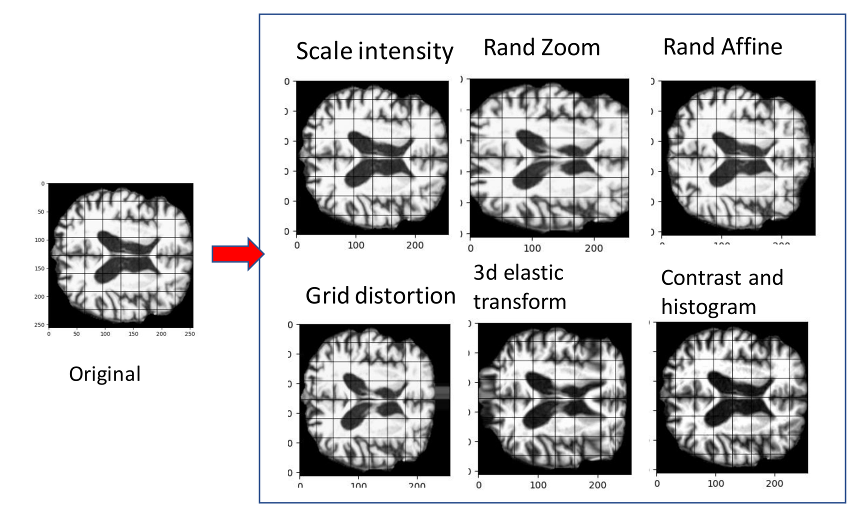
We filter the ADNI dataset for patients with both MRI and PET scans, along with their EHR data. Then we split the data into train and validation datasets while maintaining equal proportions of each class, sex, and year of scan in both sets.





Final train and validation datasets have a similar distribution of all 3 classes, and comparable mean/standard deviation values of sex, age, and MMSE score.

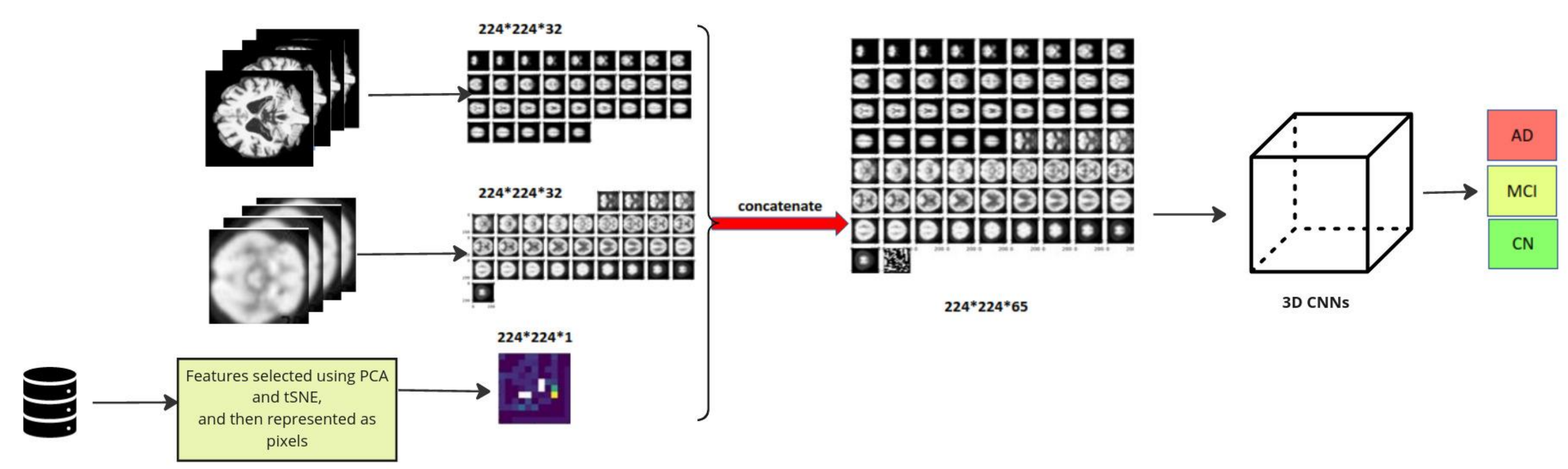
	Class Dist. (AD/MCI/CN %)	Sex Dist. (M/F %)	Age	MMSE score		
				AD	MCI	CN
Train	25.5/39/35.5	36.8/63.2	76 +- 6	21.3 +- 4.5	27.1 +- 2.8	29.0 +- 1.1
Val	25/44.2/30.8	28.8/71.2	76.2 +- 7.6	19.4 +- 3.7	26.7 +- 2.5	29.0 +- 0.8



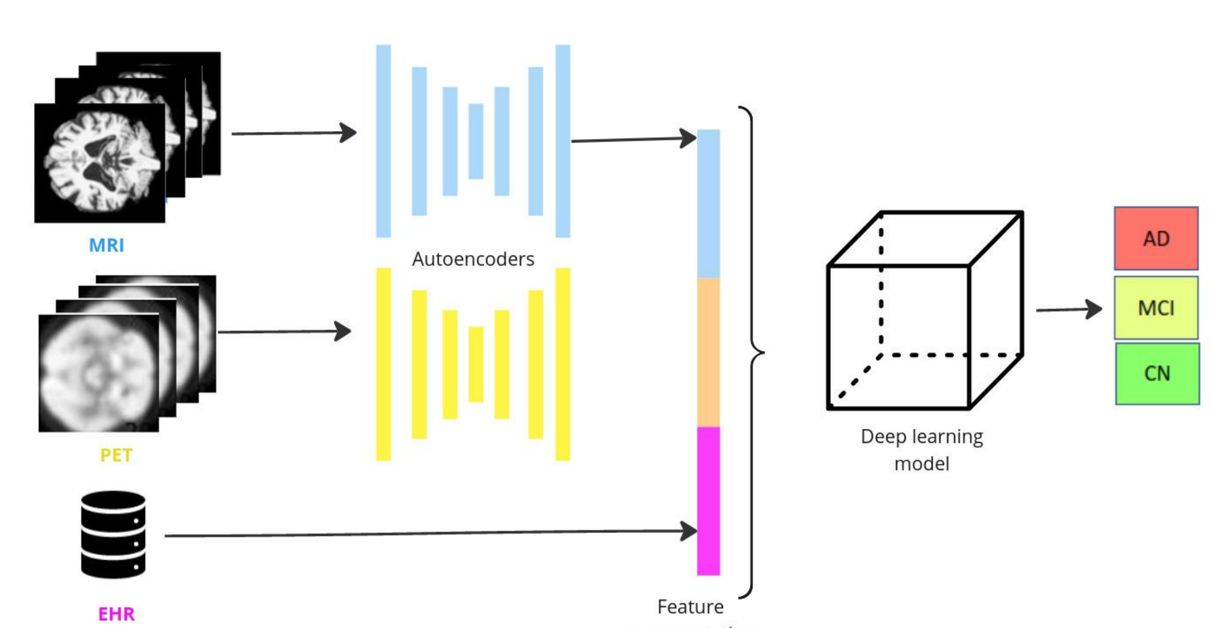
DATA FUSION METHODS / MODEL ARCHITECTURE

We focus mainly on feature-level integration in this work. We try 2 approaches:

1. EHR data as images: We use the DeepInsight approach [4] to convert EHR data from tabular to pixel input of the desired size. This EHR image feature is combined with other image data to form a single 3d image, which is passed through 3d CNNs to learn Alzheimer's disease staging.



2. Image encodings using autoencoders: we use autoencoders to learn image representations from 3d MRI and PET scans. This reduces the dimension of image features significantly, allowing them to be at the same scale as EHR for easier combination.



We finally compare performance with decision-level fusion and unimodal approaches (MRI, PET, and EHR data).

RESULTS

We measure class metrics and one vs one metrics. Our unimodal baseline achieves an accuracy of 0.697 for MRI, 0.807 for PET, and 0.817 for EHR. For the Multimodal approach, we have preliminary results for 0.701 accuracy, 0.842 AUC one vs rest, 0.820 for AUC one vs one for decision level combination.

	MRI	PET	EHR	MM (Decision level fusion)
Accuracy	0.697	0.807	0.817	0.701
AD accuracy	0.619	0.8	0.687	0.667
CN accuracy	1.0	0.778	0.775	0.806
MCI accuracy	0.428	0.826	0.885	0.6
AD vs CN	0.866	0.931	0.978	0.912
AD vs MCI	0.762	0.860	0.852	0.843
CN vs MCI	0.777	0.875	0.918	0.727
AUC One vs Rest	0.769	0.917	0.94	0.842
AUC One vs One	0.718	0.924	0.927	0.820

Work in [5] achieves AD vs CN accuracy of 81.9 on MRI and 84.5 for PET scan. Using multimodal (MRI + PET) they achieve an accuracy of 84.6. Work in [3] achieves AD vs CN accuracy of 0.89 for multimodal (MRI + EHR), but for only 2 classes. Our one vs one accuracy is competitive with previous baselines.

	[5]			[3]			Ours			
Modality	MRI + PET			MRI + EHR			MRI / PET/ EHR			
Classes	AD vs MCI vs CN			CN vs AD			AD / CN/ MCI			
	MRI	PET	MM	MRI	EHR	MM	MRI	PET	EHR	MM
AD vs CN	0.819	0.845	0.846			0.89	0.866	0.931	0.978	0.912
AD vs MCI	-	-	-				0.762	0.860	0.852	0.843
CN vs MCI	-	-	-				0.777	0.875	0.918	0.727
CN vs rest	0.825	0.859	0.864							
AUC	-	-	-			0.94	0.769	0.917	0.94	0.842

CONCLUSION

Multiple modalities can provide complementary information to learn the same task. This can help boost the performance of deep learning models. Combining the different kinds of imaging and tabular data can be challenging. In this work, we propose two methods to combine imaging and EHR data and learn to classify Alzheimer's disease stage.

REFERENCES

[1] Venugopalan, J., Tong, L., Hassanzadeh, H. R. & Wang, M. D. Multimodal deep learning models for early detection of Alzheimer's disease stage. *Sci. Rep.* **11**, 3254 (2021).

[2] Bae, J. B. *et al.* Identification of Alzheimer's disease using a convolutional neural network model based on T1-weighted magnetic resonance imaging. *Sci. Rep.* **10**, 22252 (2020).

[3] El-Sappagh, S., Alonso, J. M., Islam, S. M. R., Sultan, A. M. & Kwak, K. S. A multilayer multimodal detection and prediction model based on explainable artificial intelligence for Alzheimer's disease. *Sci. Rep.* **11**, 2660 (2021).

[4] Sharma, A., Vans, E., Shigemizu, D., Boroevich, K. A. & Tsunoda, T. DeepInsight: A methodology to transform a non-image data to an image for convolution neural network architecture. *Sci. Rep.* **9**, 11399 (2019).

[5] Lu, D. *et al.* Multimodal and Multiscale Deep Neural Networks for the Early Diagnosis of Alzheimer's Disease using structural MR and FDG-PET images. *Sci. Rep.* **8**, 5697 (2018)