Prediction Model for Alzheimer's Disease

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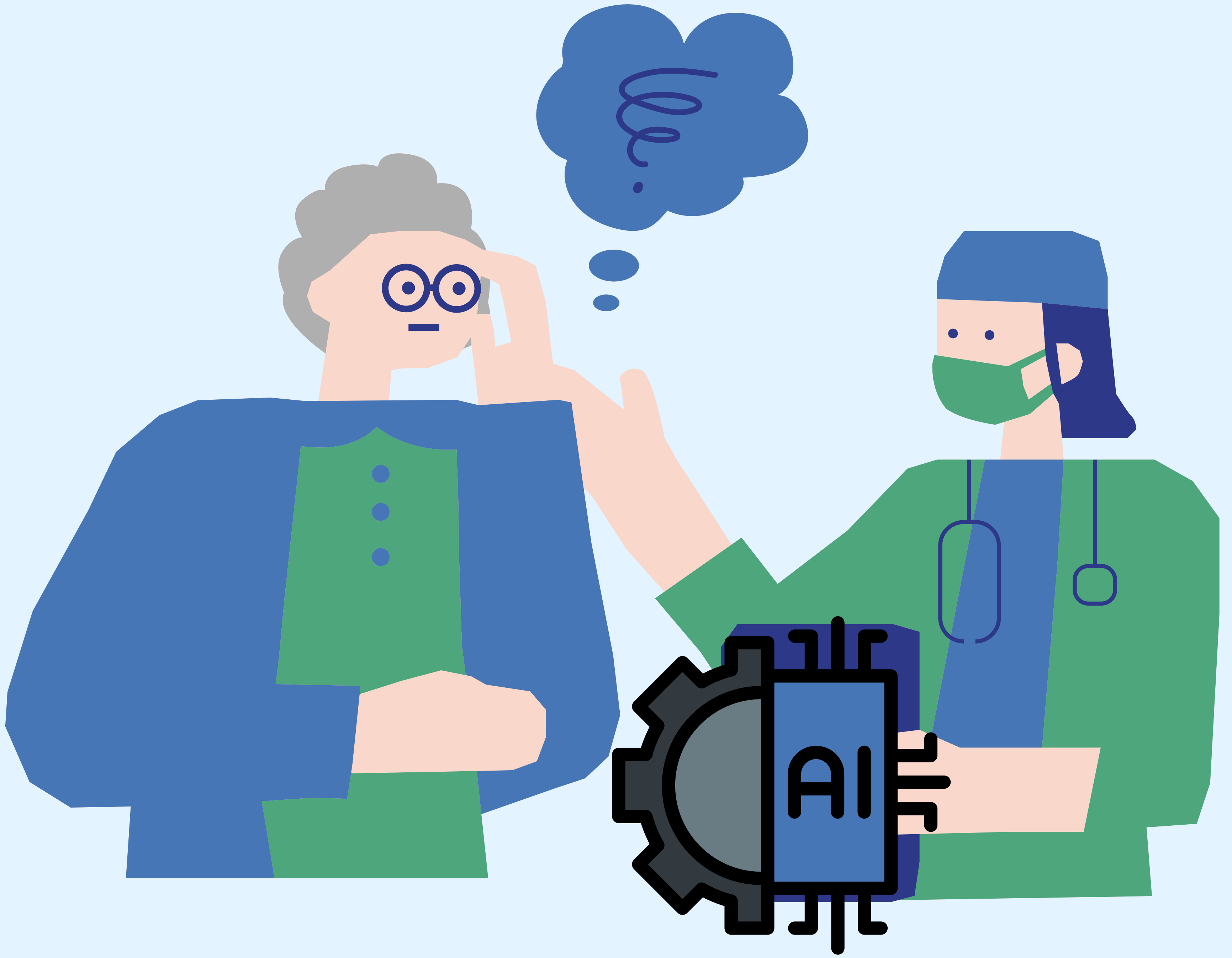
CompSci 109A Final Project, Fall 2023



Problem Statement

Can we accurately predict a **dementia diagnosis** in patients using demographic and clinical factors from the ADNI dataset?

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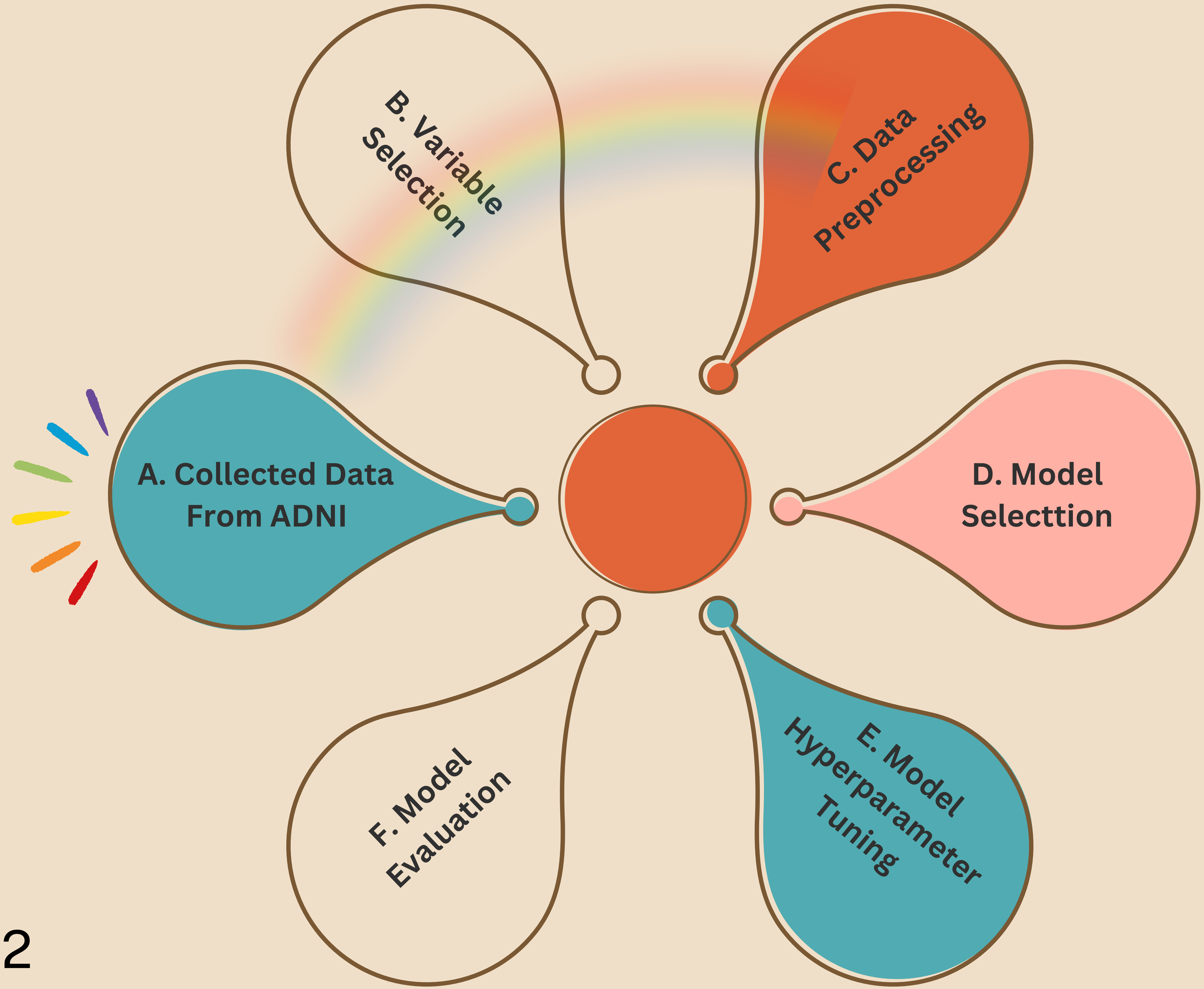
02 EDA
03 Modeling
04 Training details
05 Results
06 Conclusion
07 Future Work



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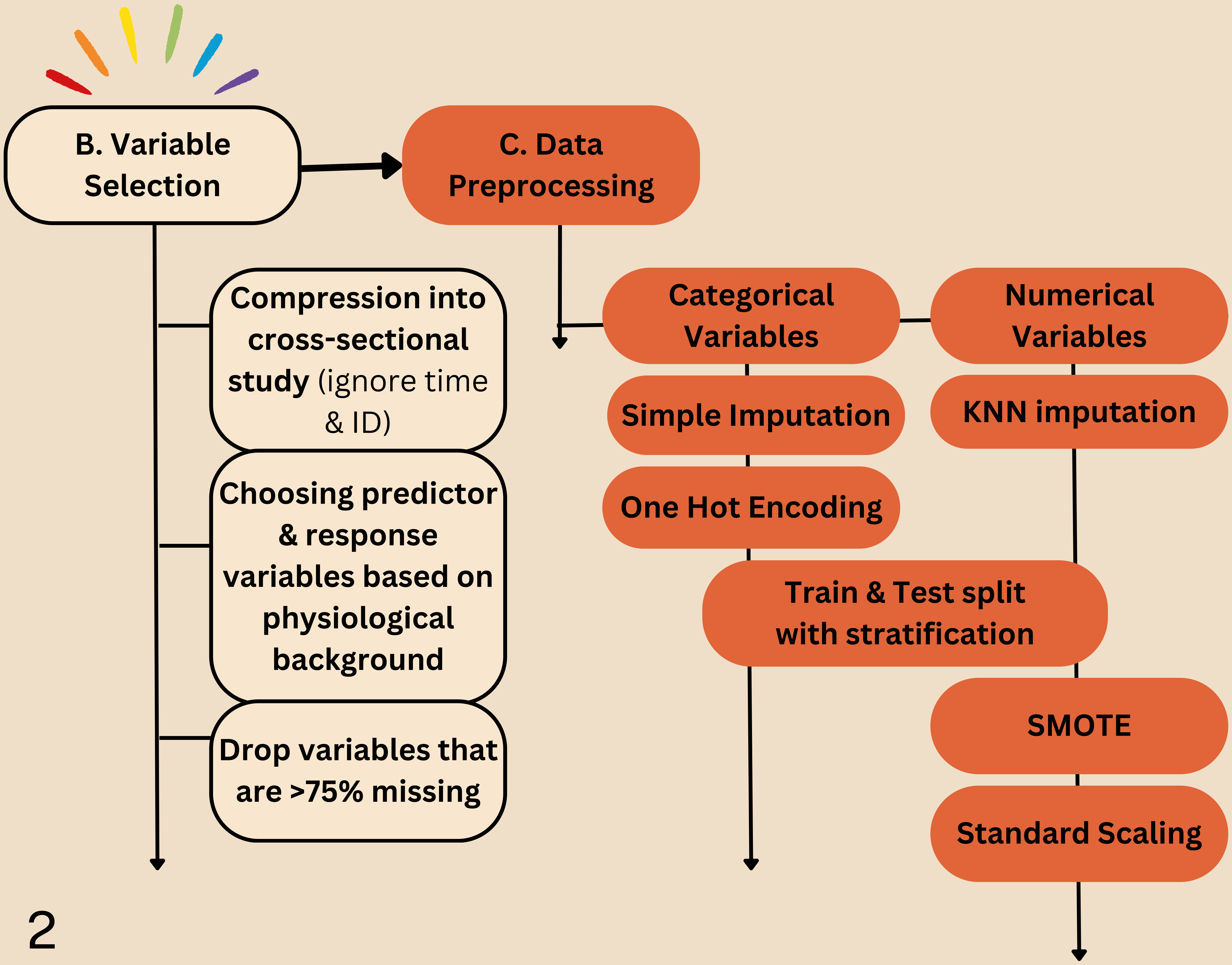

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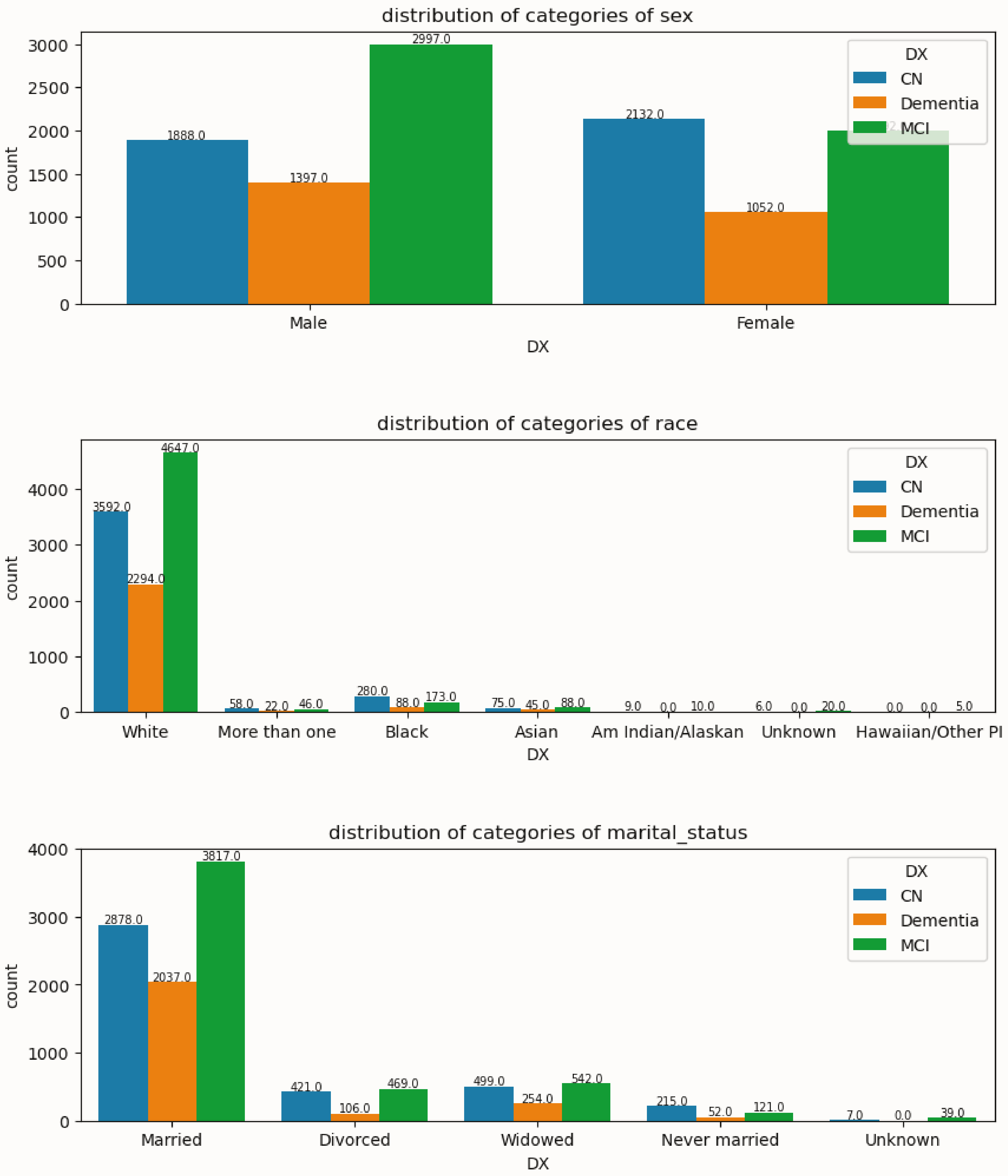
Variable Distribution



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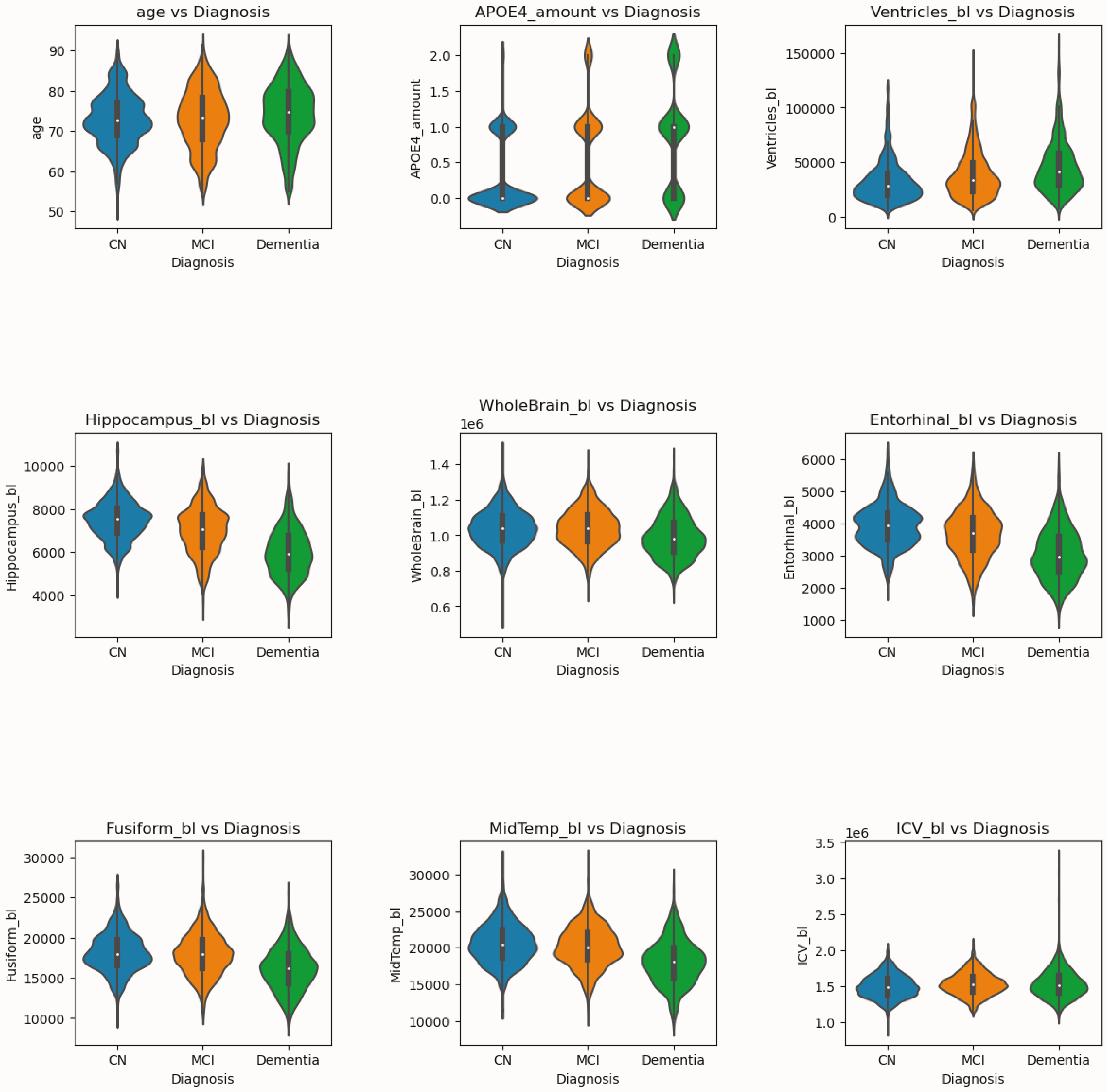

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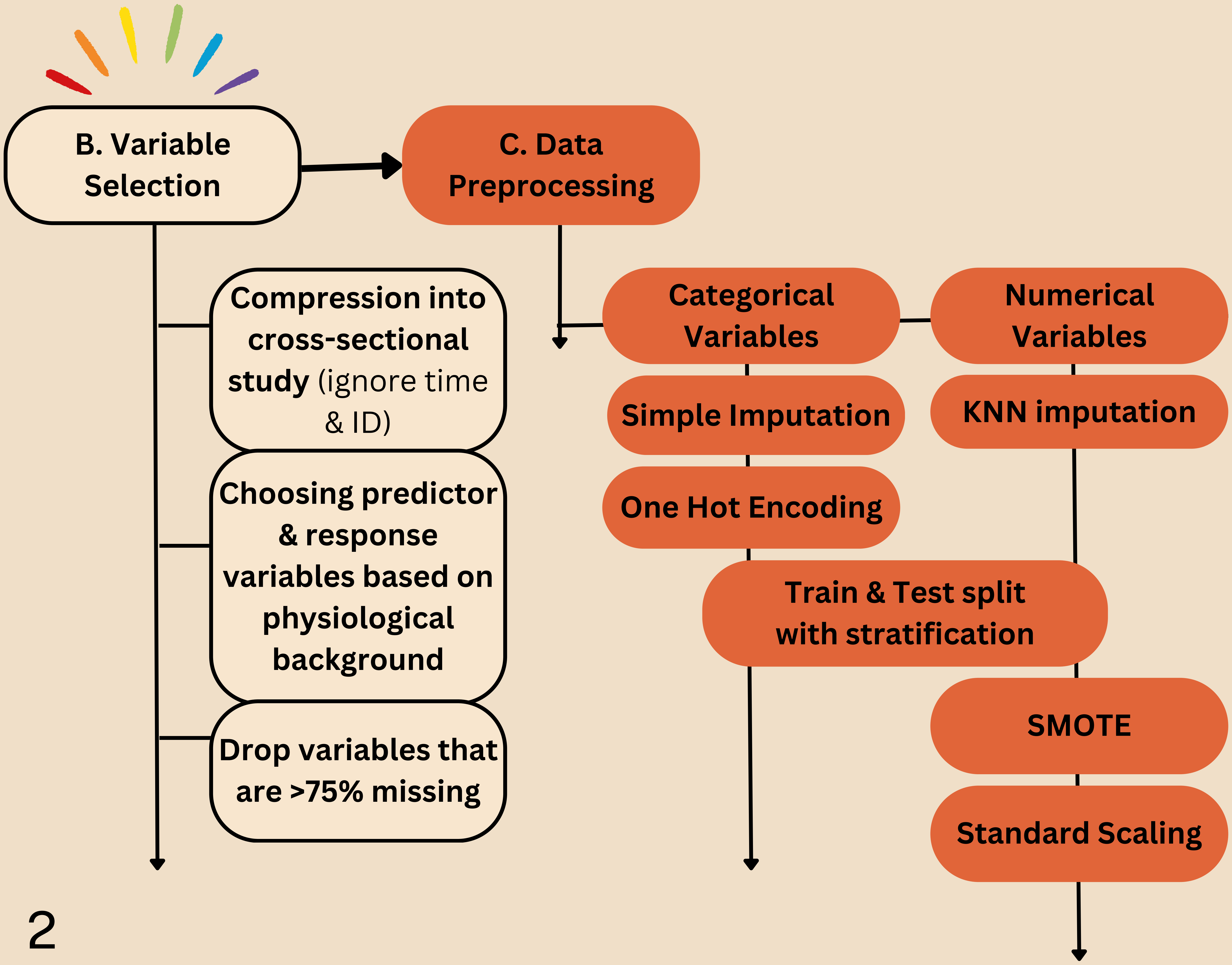

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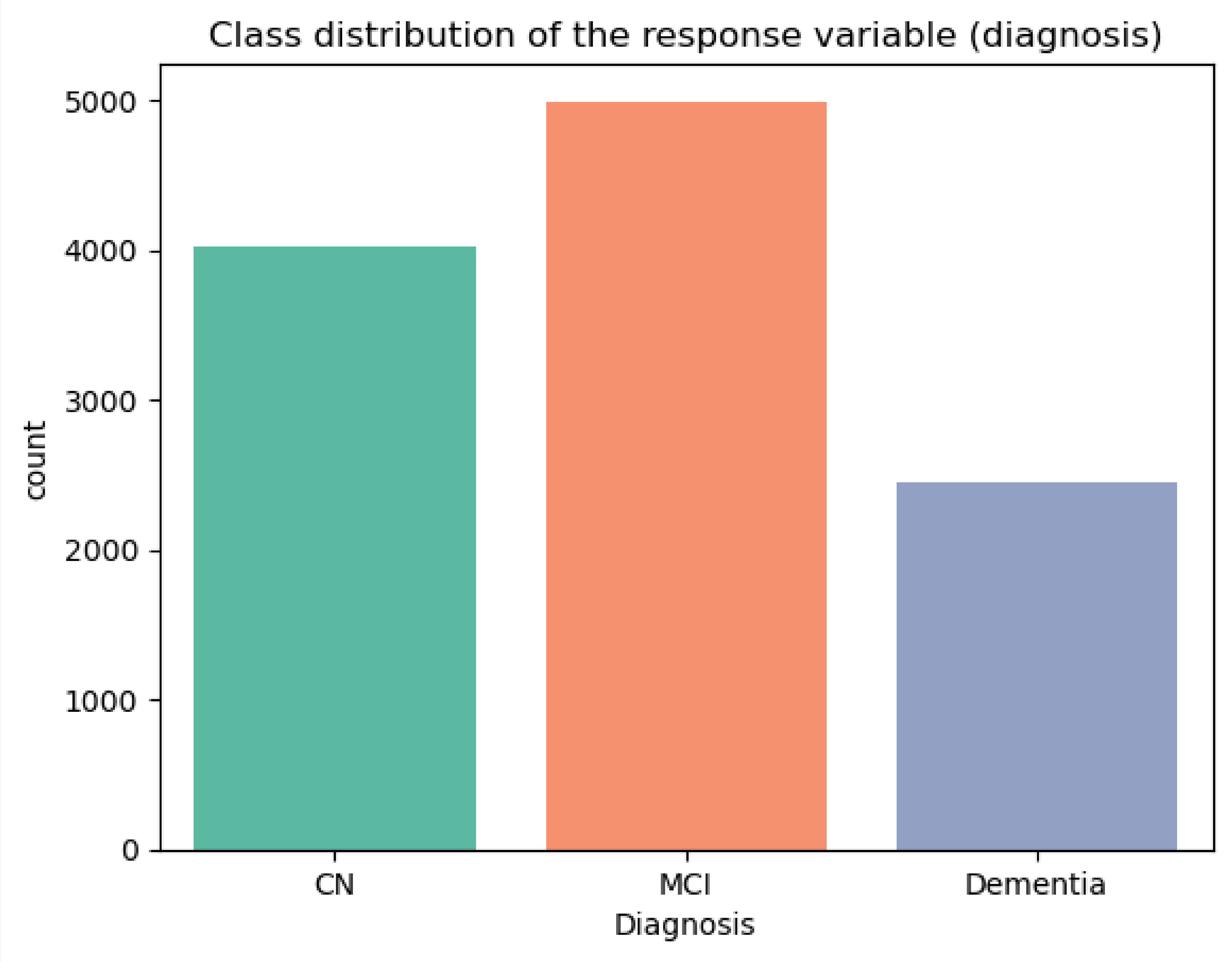

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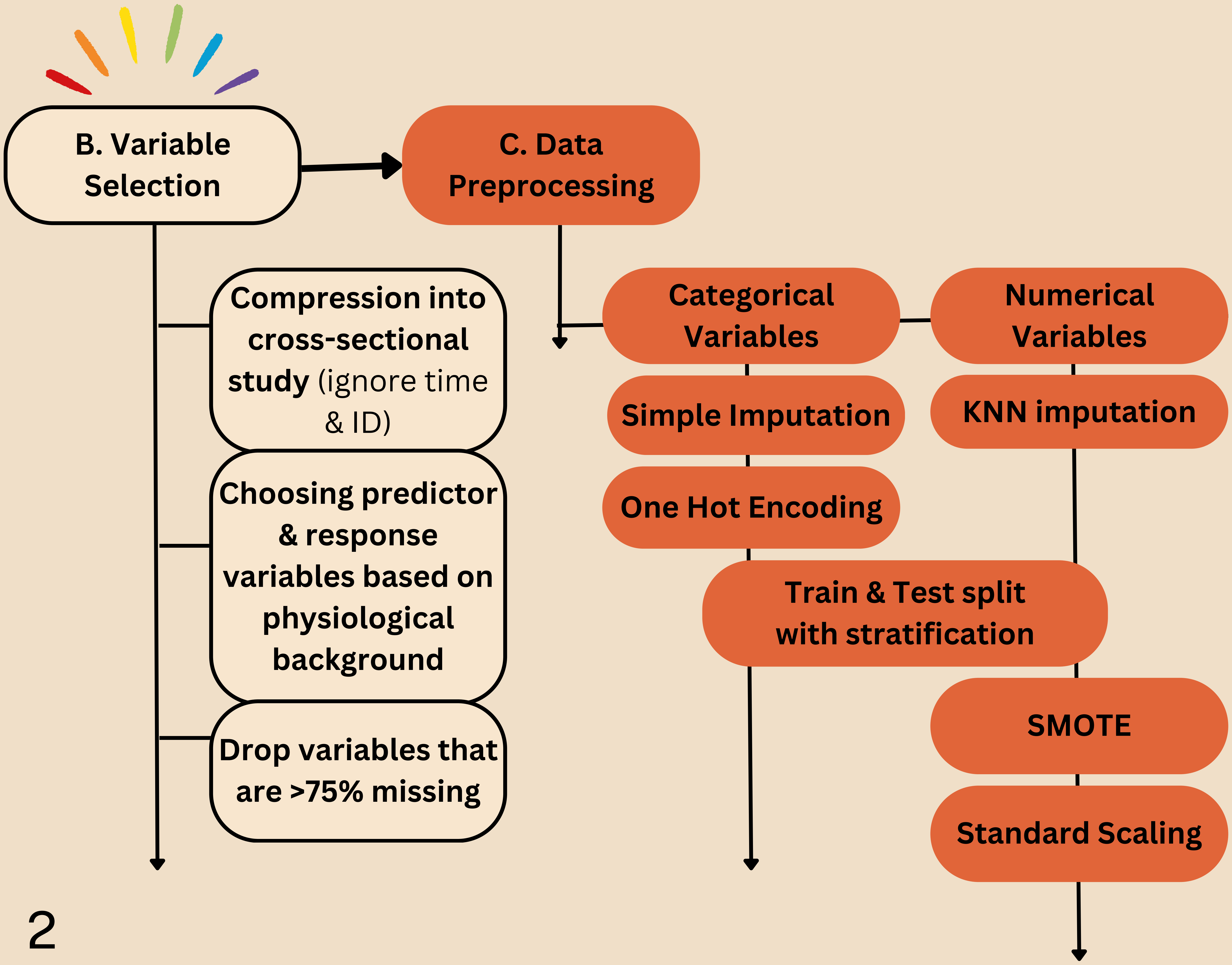

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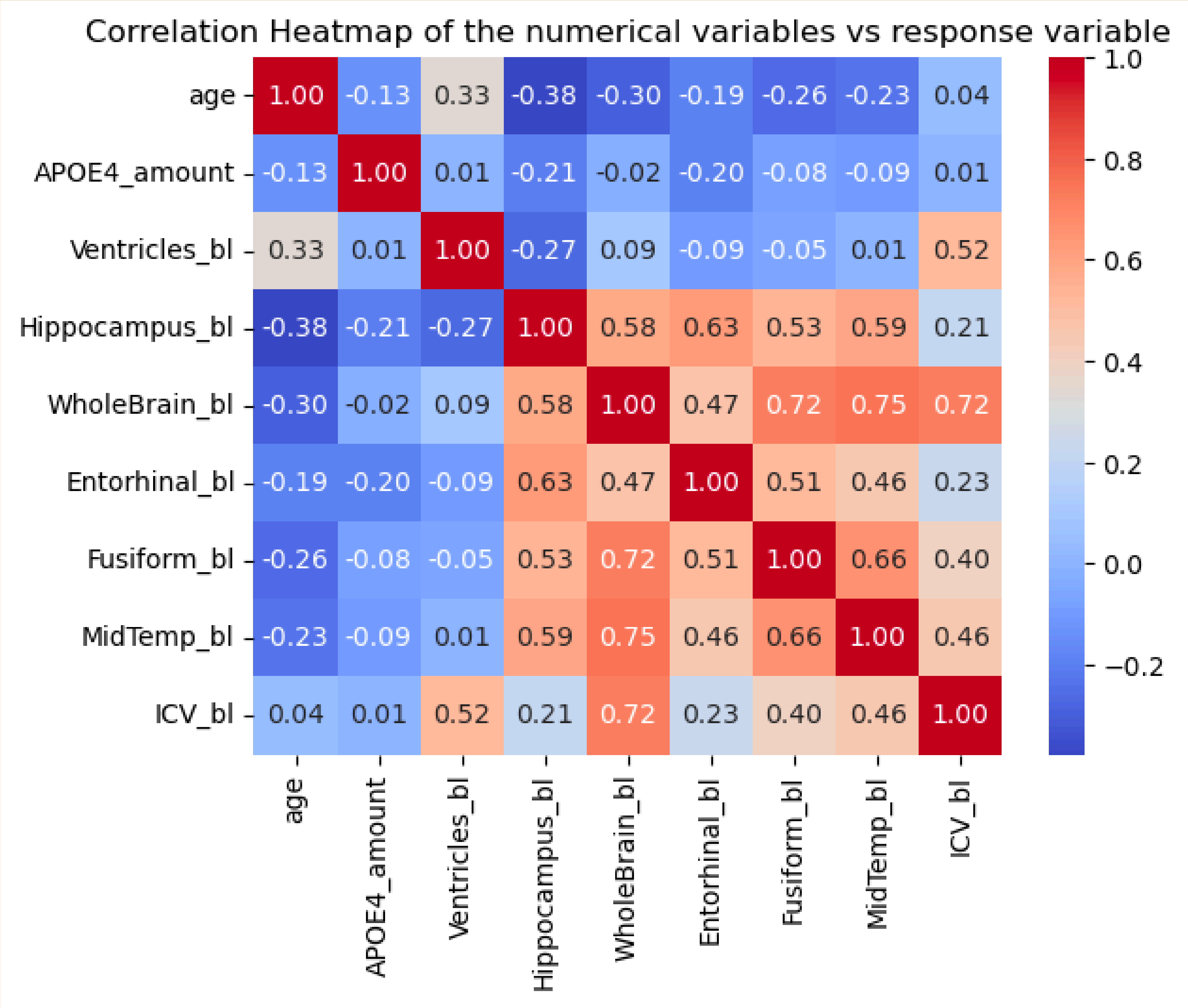

Confounding Variables

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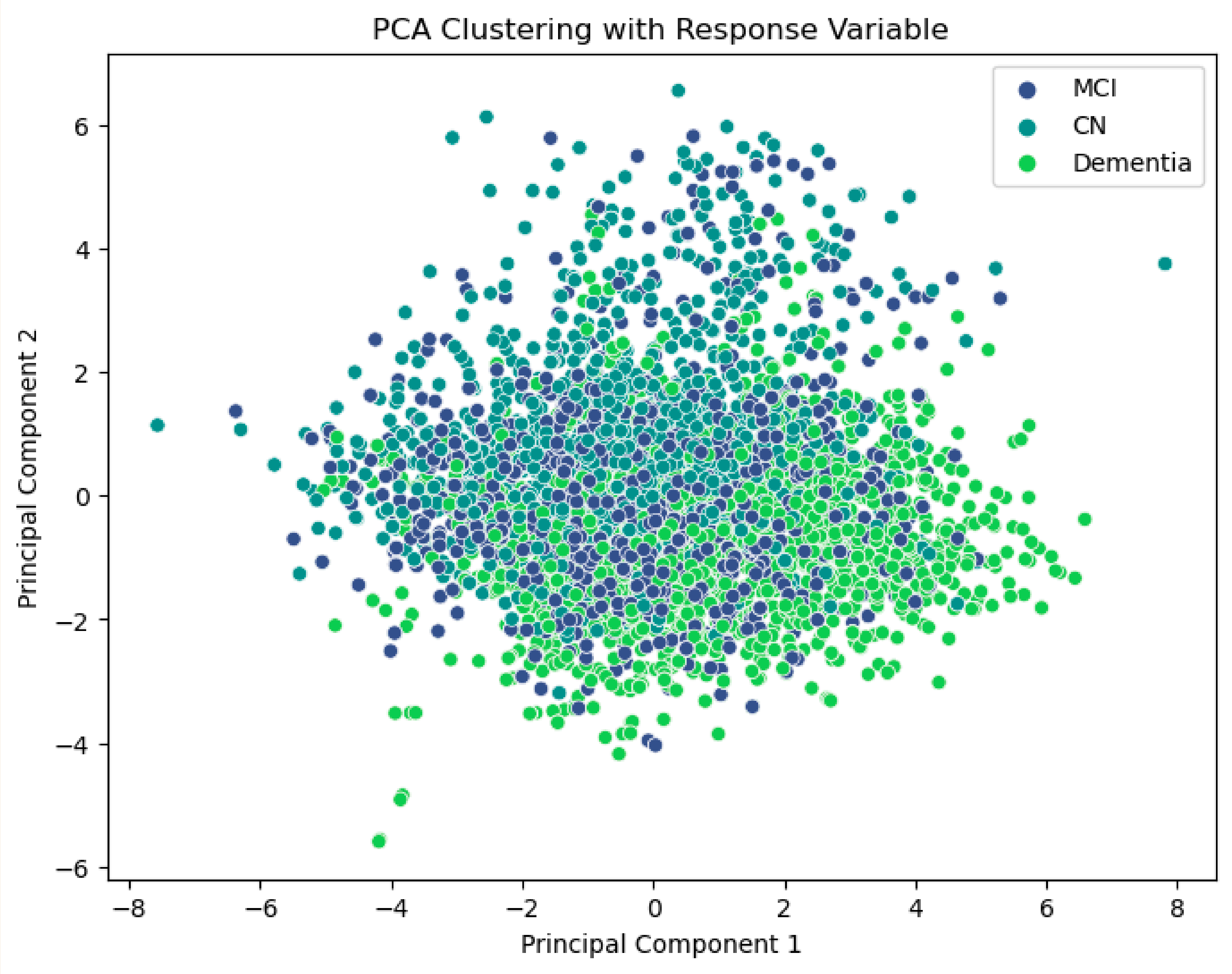

PCA/t-SNE

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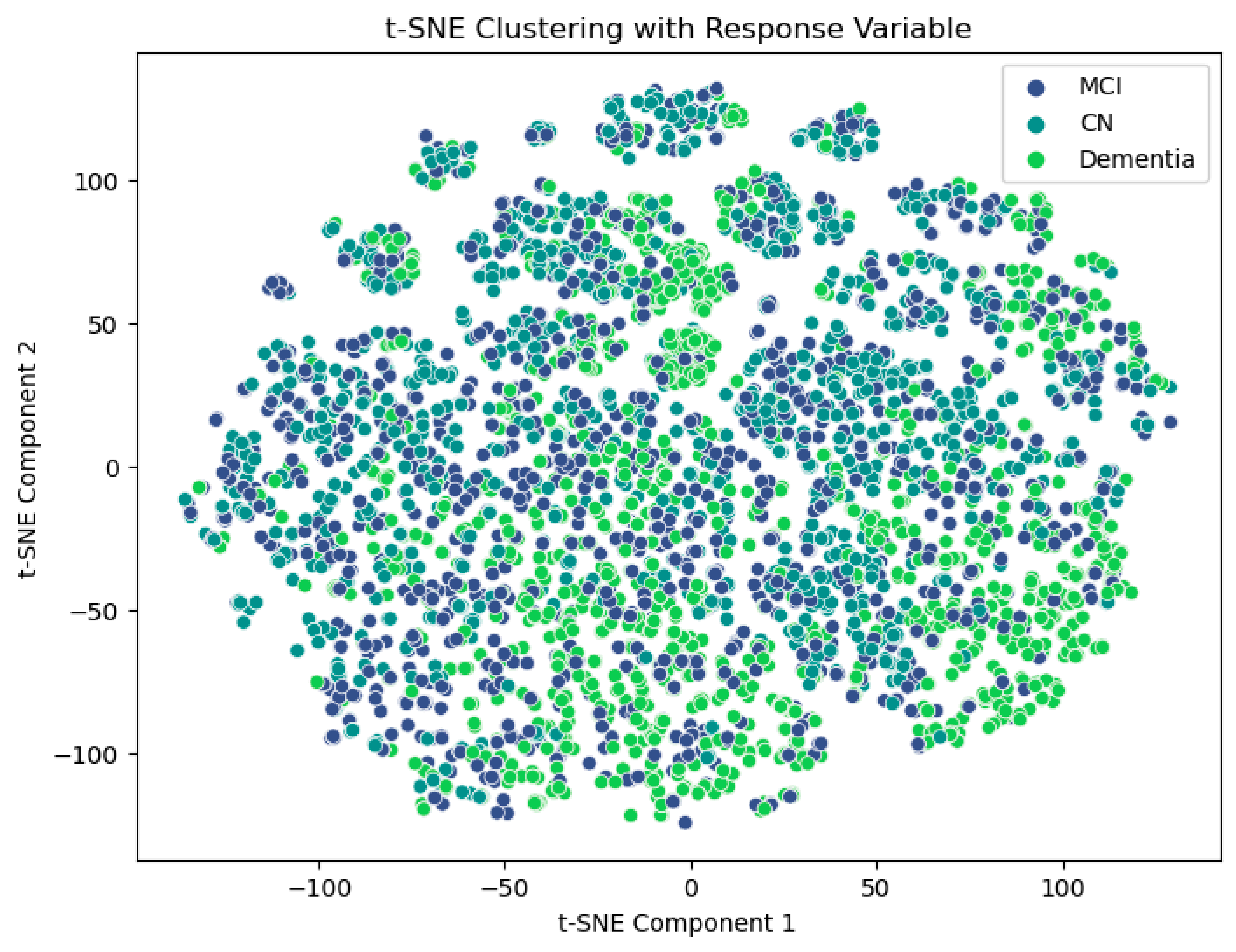

PCA / t-SNE

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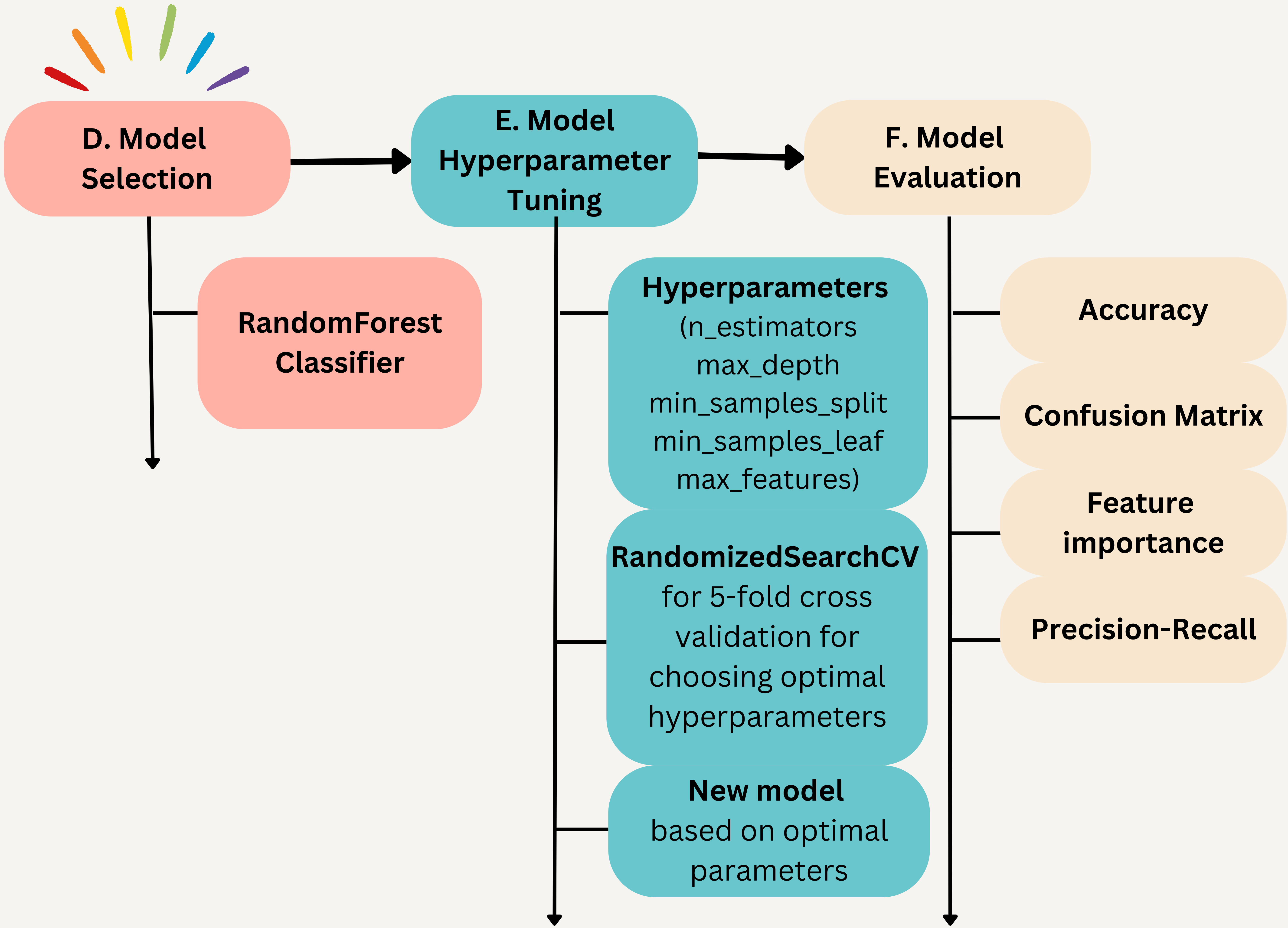

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94 seconds

Hyperparameters

n_estimators	50
max_depth	None
min_samples_split	55
min_samples_leaf	1
max_features	sqrt

	F1 Score
Train	0.91
Test	0.83

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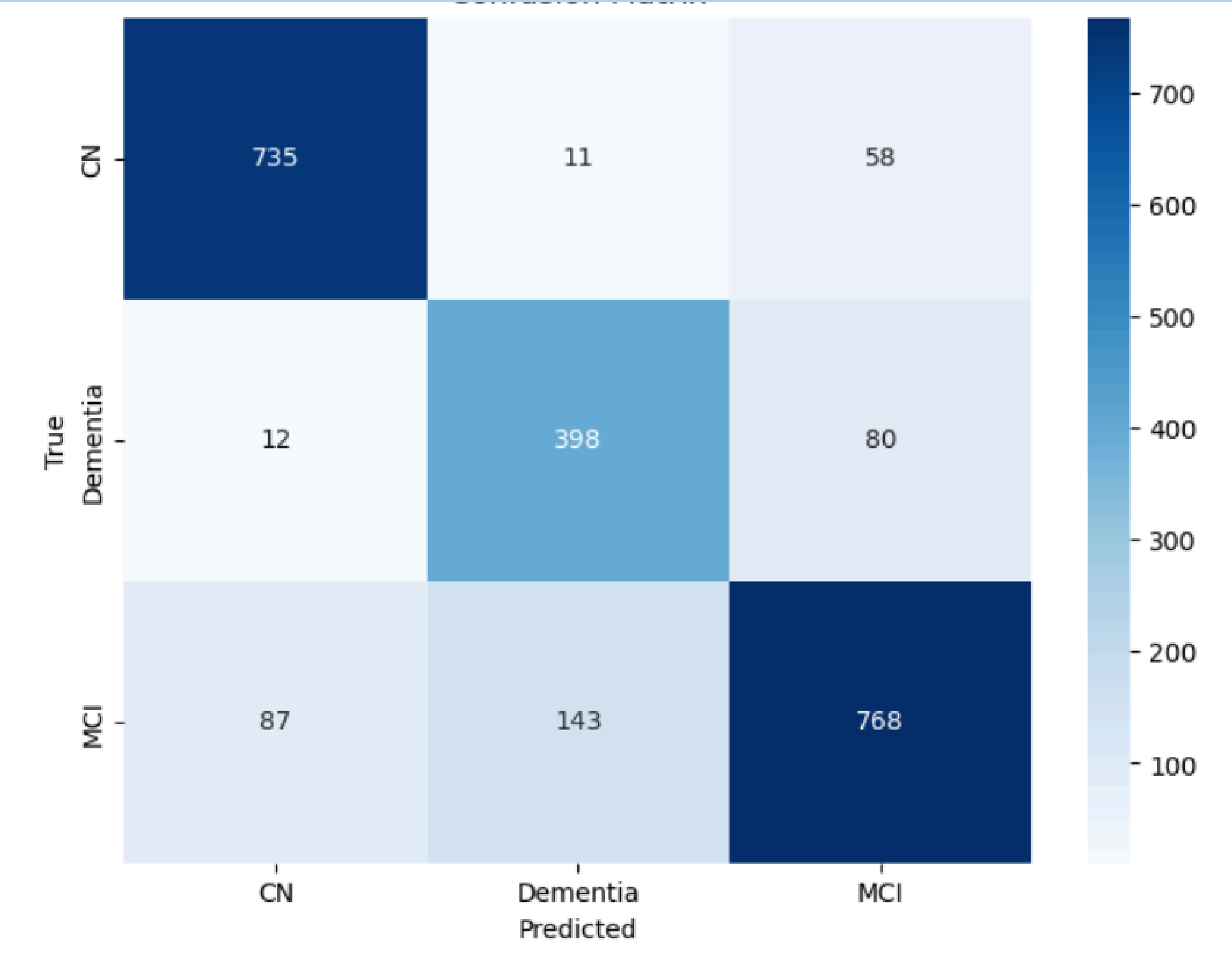
Confusion Matrix



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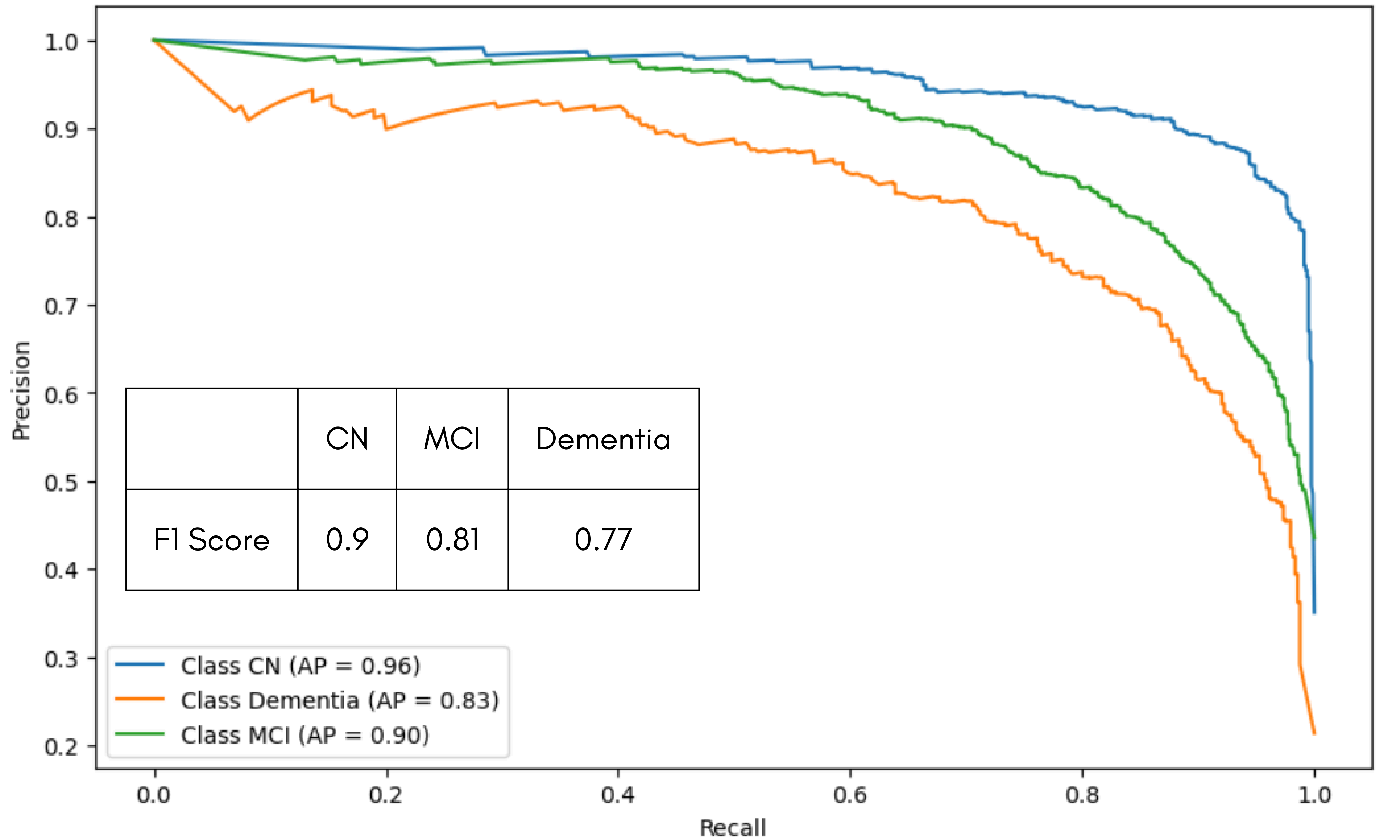
Precision Recall Curve



	CN	MCI	Dementia
F1 Score	0.9	0.81	0.77

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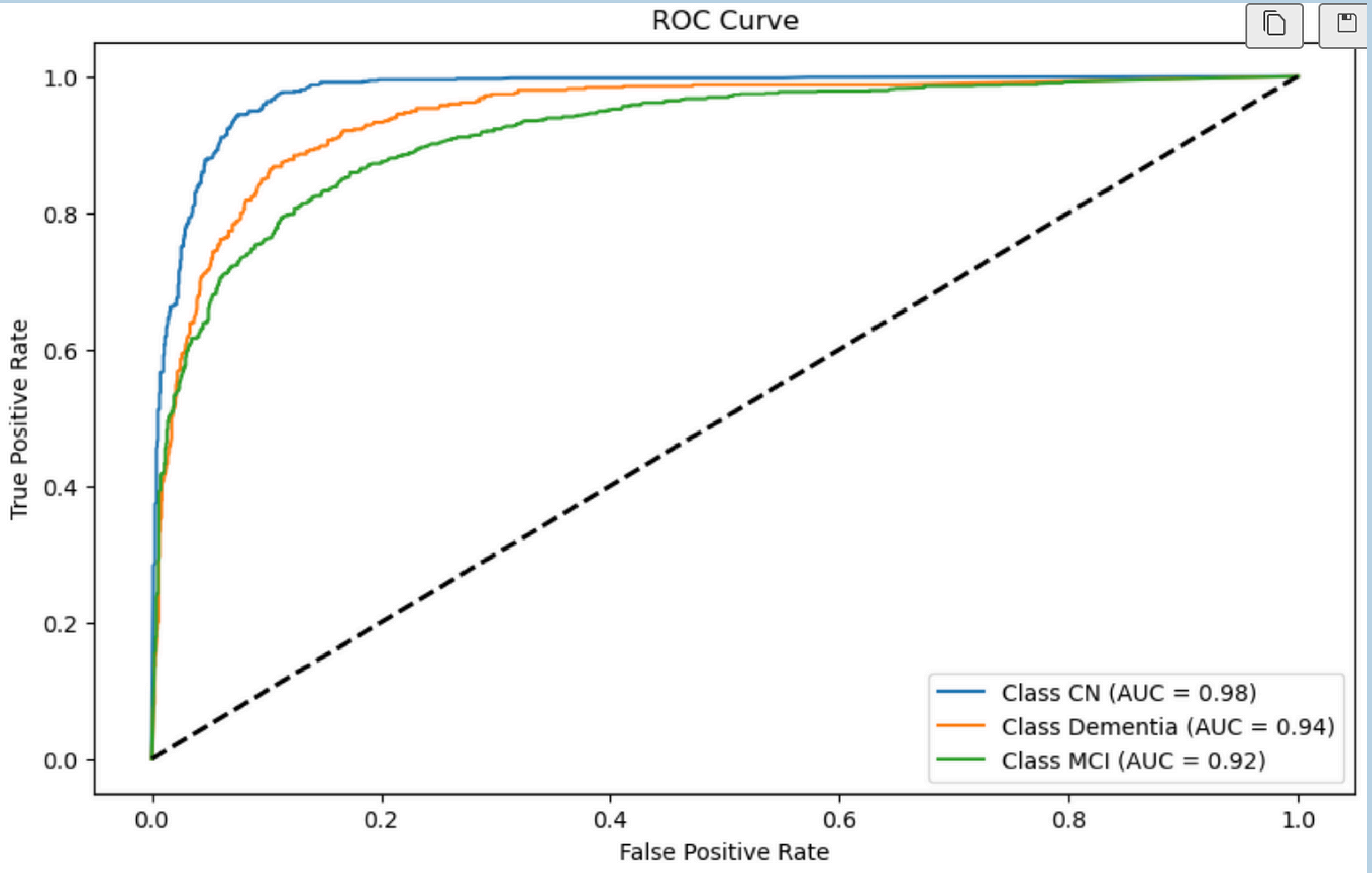
ROC Curve



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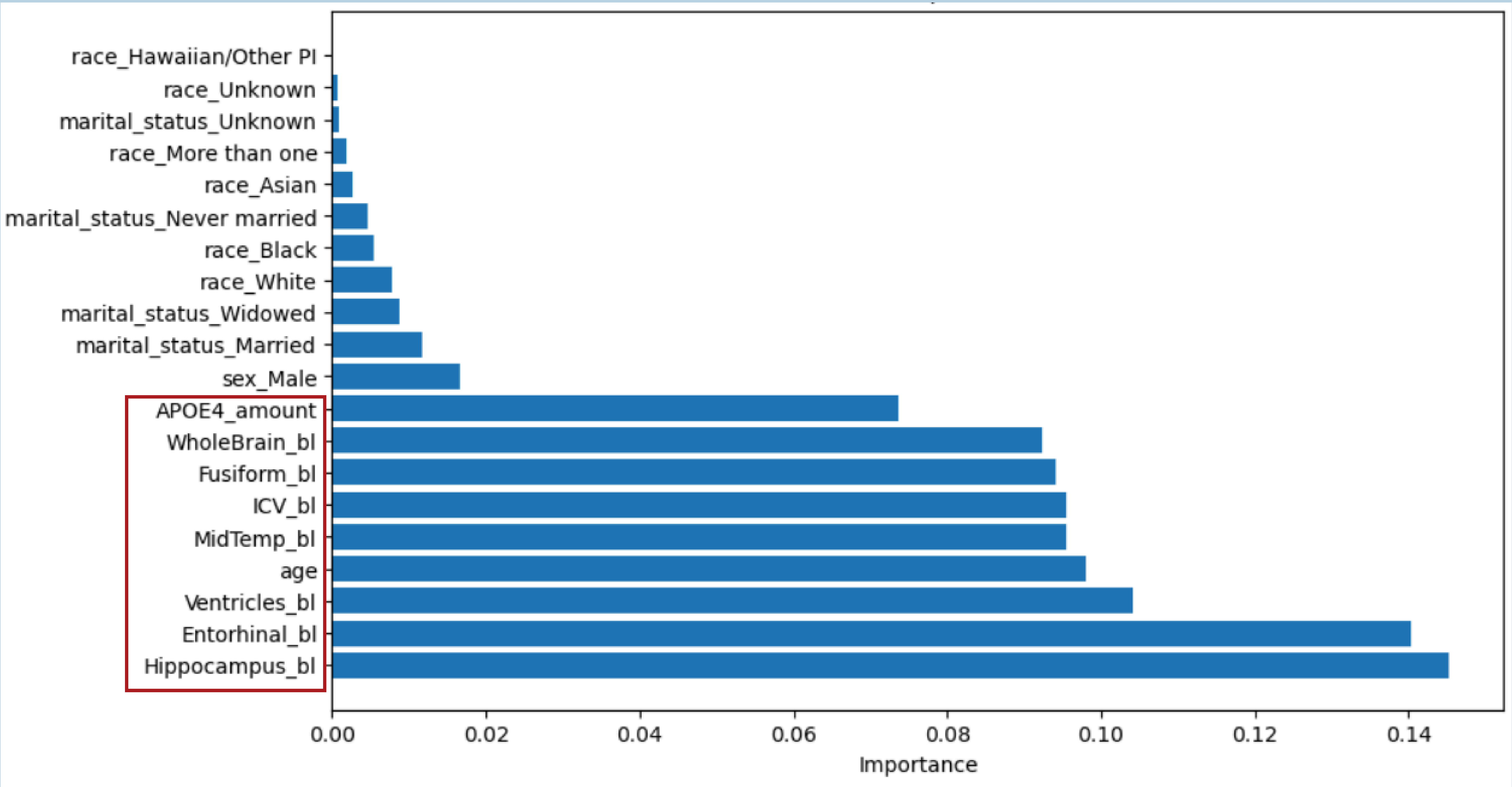
Feature Importance



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Main Takeaways

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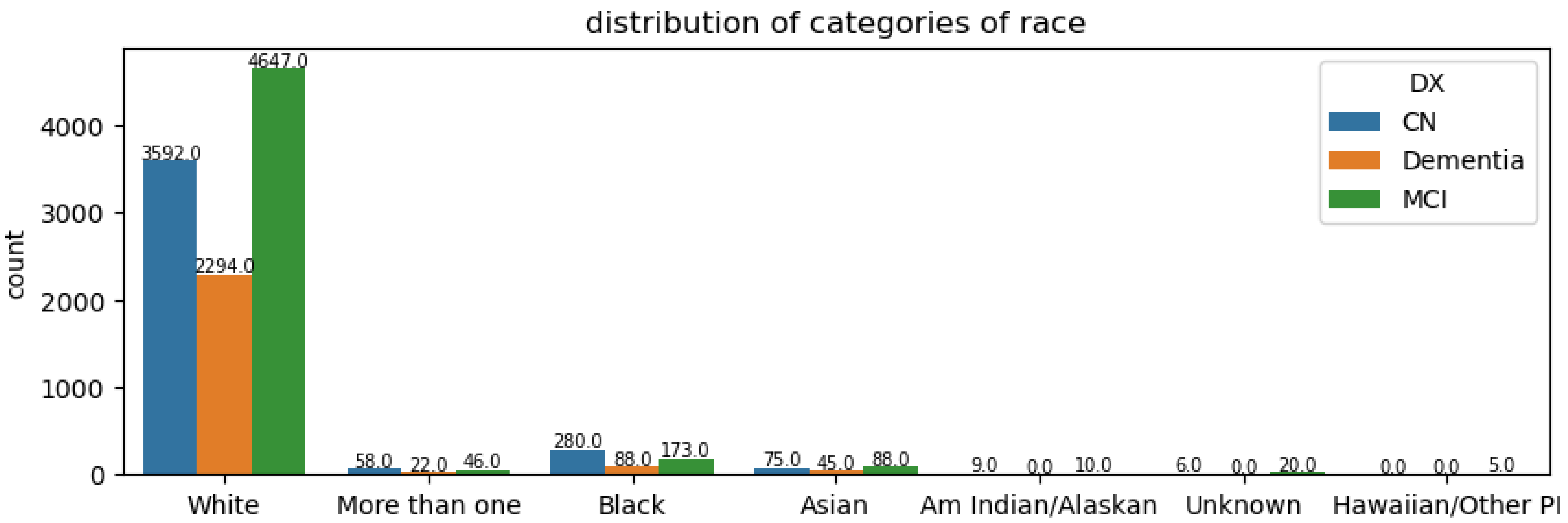
→ Most important features are brain region size, age, and APOE4 expression

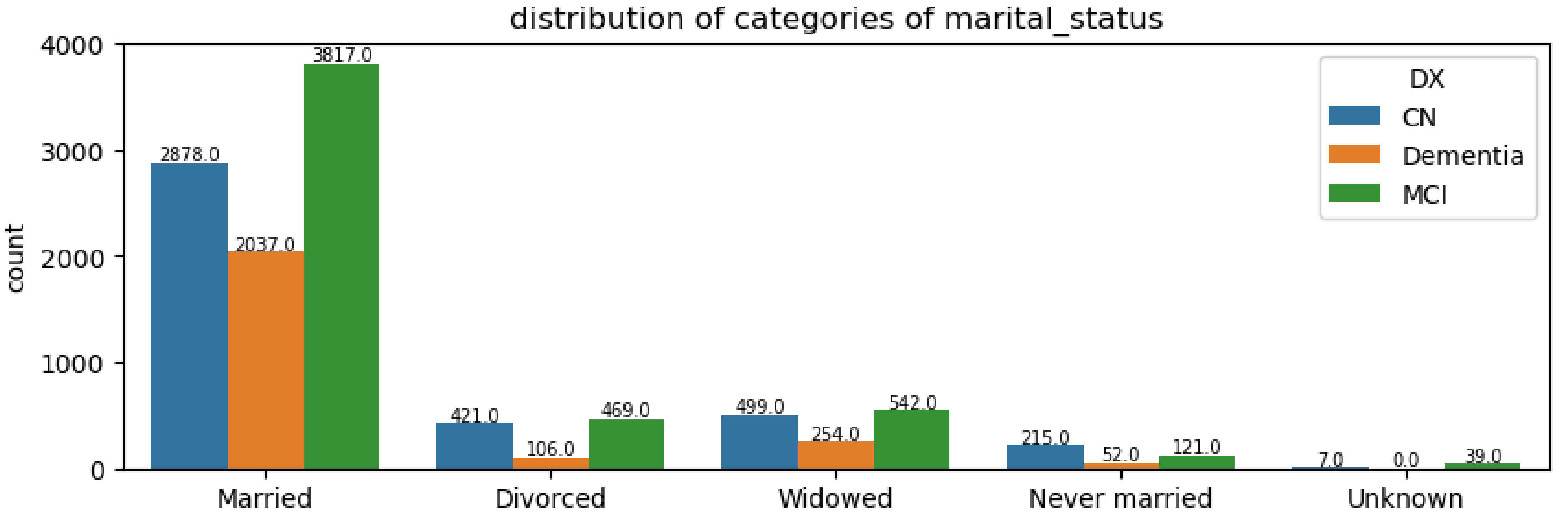
→ Model should include APOE4 gene expression when predicting diagnosis

→ Model had less efficient with balancing precision and recall for dementia (compared to MCI and CN)

Model was a ***very good*** classifier based on dementia ROC AUC score of 0.94

LIMITATIONS





“white” and “married” are both **overrepresented** and have the highest feature importance of their groups.

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SAMPLING TECHNIQUES

Cluster-Based Oversampling to **augment data**

He, H., Bai, Y., Garcia, E. A., & Li, S. (2008).
Jo, T., & Japkowicz, N. (2004).

BIAS MITIGATION ALGORITHMS

Pre-processing and in-processing techniques to **reduce bias**, such as reweighting and adversarial debiasing

Kamiran, F., & Calders, T. (2012).
Zhang, B. H., Lemoine, B., & Mitchell, M. (2018).

MODEL INTERPRETATION

Methods like SHAP for model **output explanations**

Lundberg, S. M., & Lee, S.-I. (2017).

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References

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- Jo, T., & Japkowicz, N. (2004). Class imbalances versus small disjuncts. ACM SIGKDD Explorations Newsletter, 6(1), 40-49. ACM Digital Library.
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- Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. arXiv preprint arXiv:1705.07874. arXiv.

THANK YOU