

# NeuroSTORM: Towards a general-purpose foundation model for fMRI analysis

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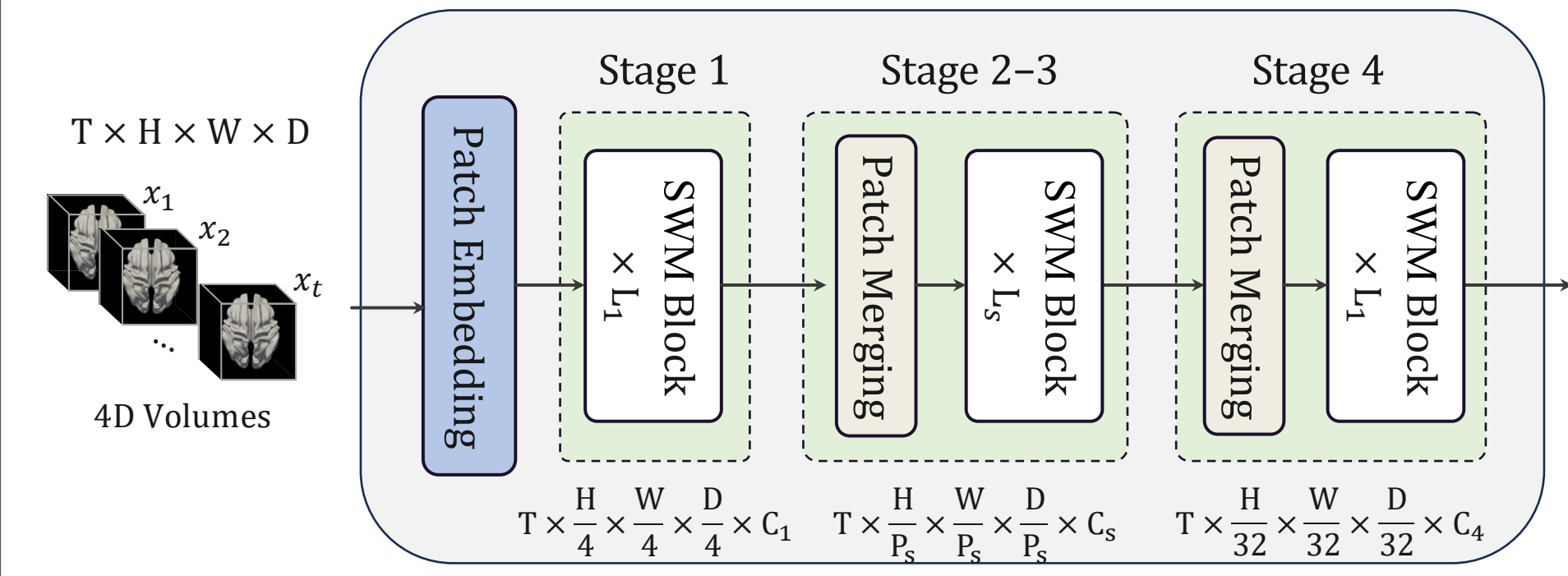


## Introduction

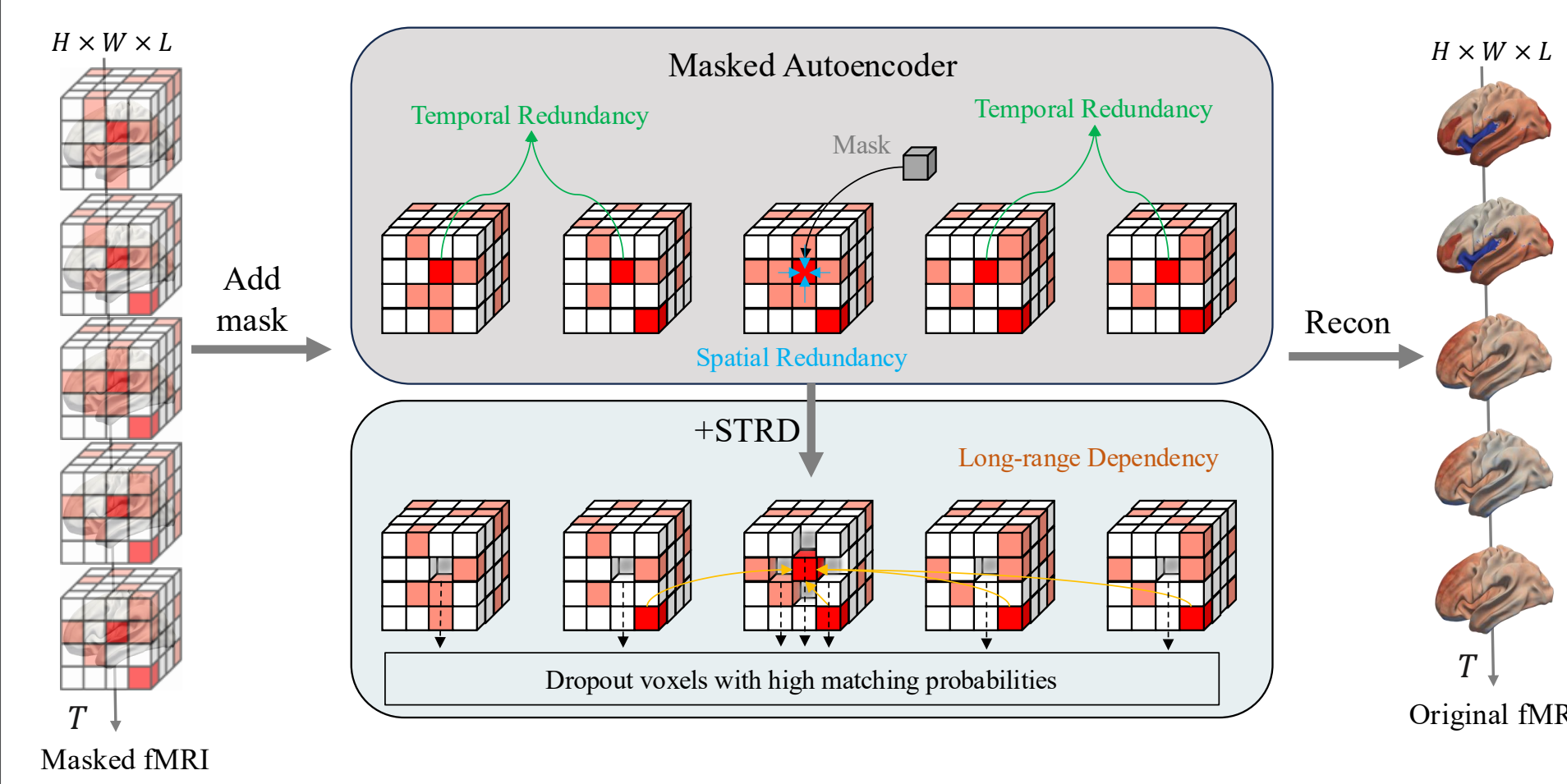
- The broader impact of functional MRI (fMRI) remains limited by challenges in **reproducibility** and **transferability**.
- Medical **foundation models** show promise for addressing these challenges through scalable pretraining and cross-task generalization.
- We propose a **fMRI foundation model "NeuroSTORM"** pretrained on >65k scans, featuring 1) Shifted-Window Mamba backbone for efficient 4D processing, 2) Spatiotemporal Redundancy Dropout to mitigate redundancy in voxel-wise signals, and 3) Task-specific Prompt Tuning for parameter-efficient adaptation.
- We constructed a comprehensive, independent **benchmark of five tasks** to evaluate the performance of NeuroSTORM.

## Methods

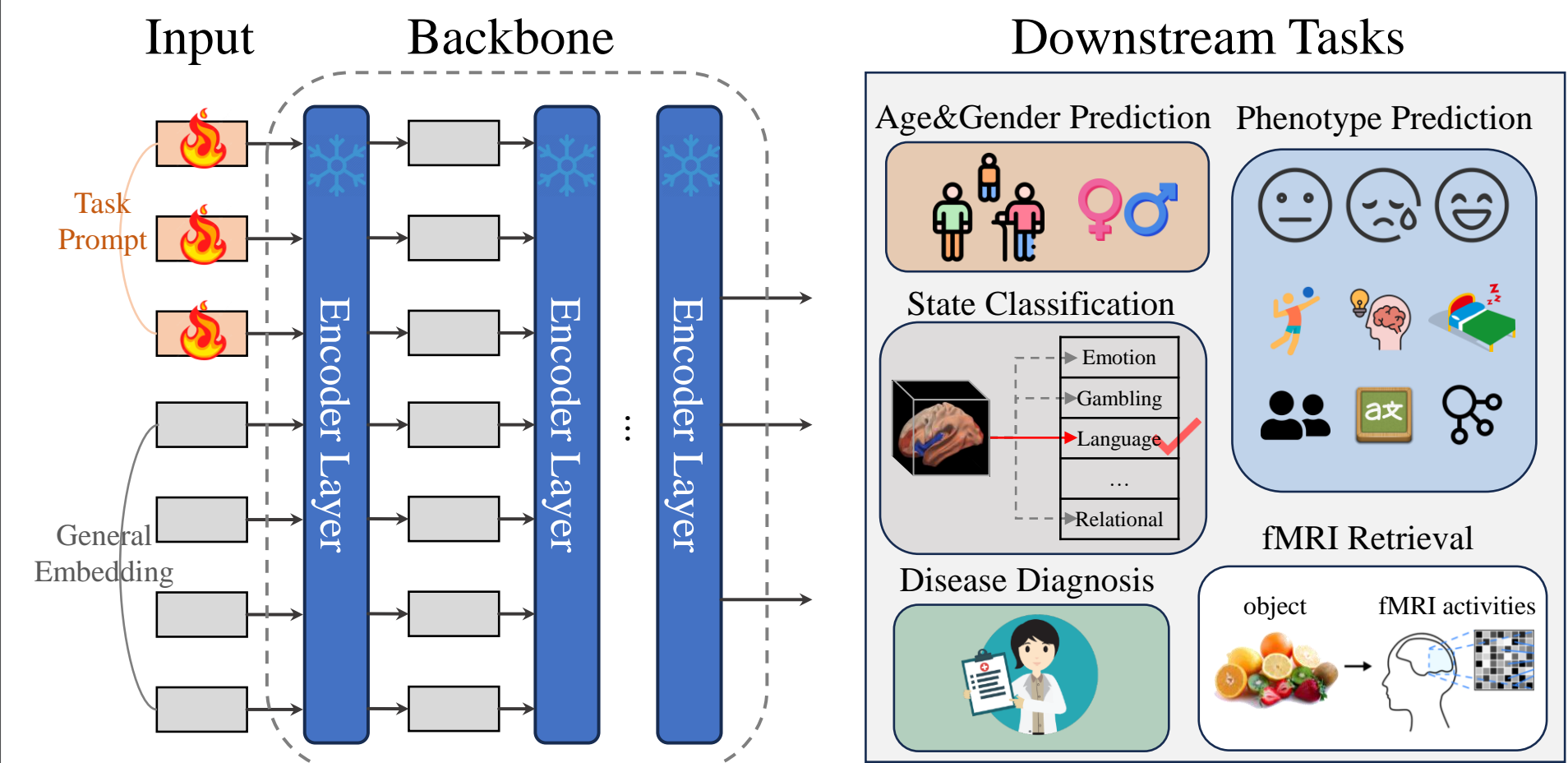
NeuroSTORM is built on a **Shifted-Window Mamba backbone**, which efficiently processes 4D fMRI volumes



The **Spatiotemporal Redundancy Dropout module** encourages the model to focus on capturing complex long-range relationships within 4D fMRI sequences

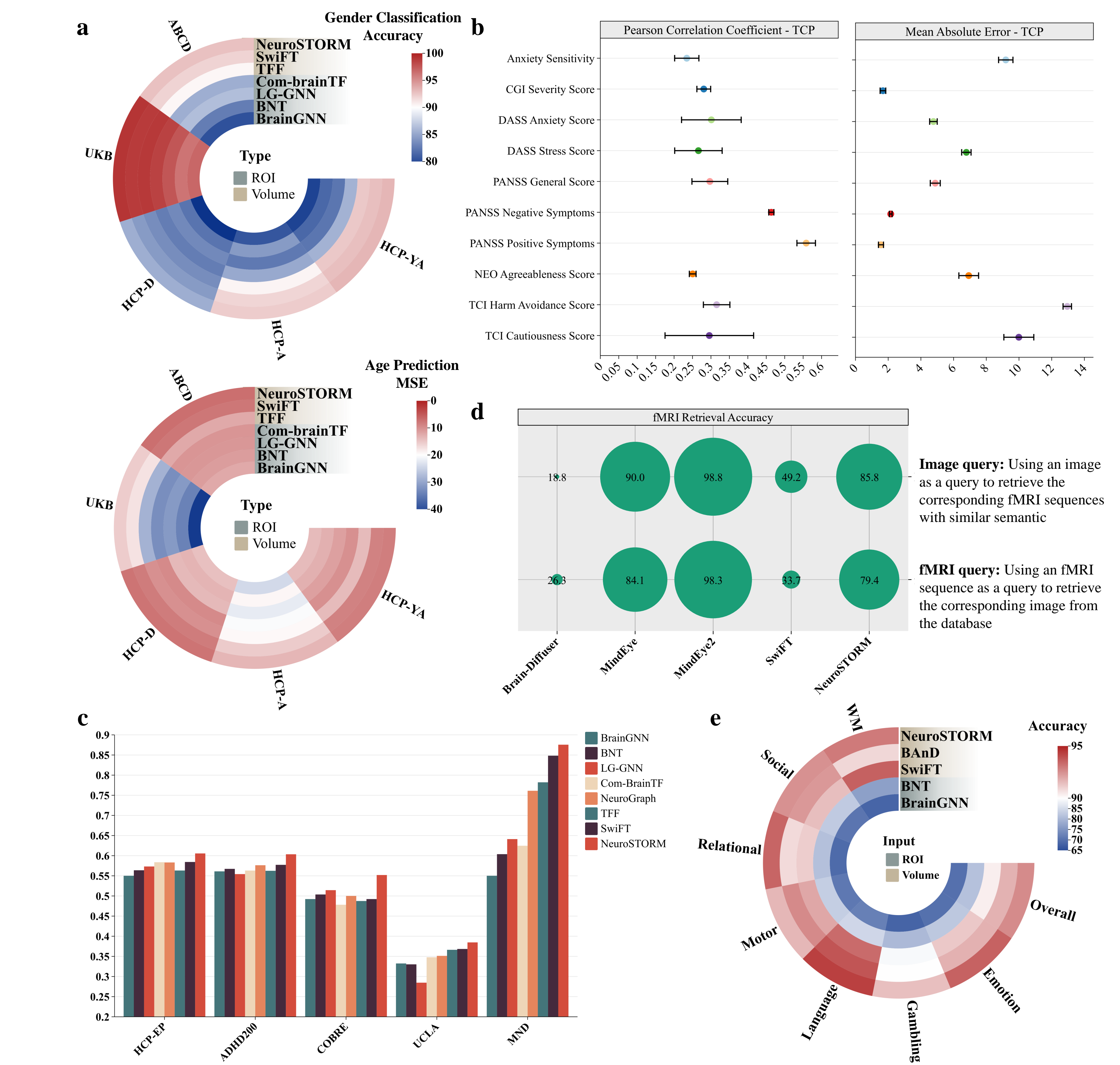


**Task-specific Prompt Tuning** introduces learnable prompt parameters for each downstream task while keeping the backbone parameters fixed



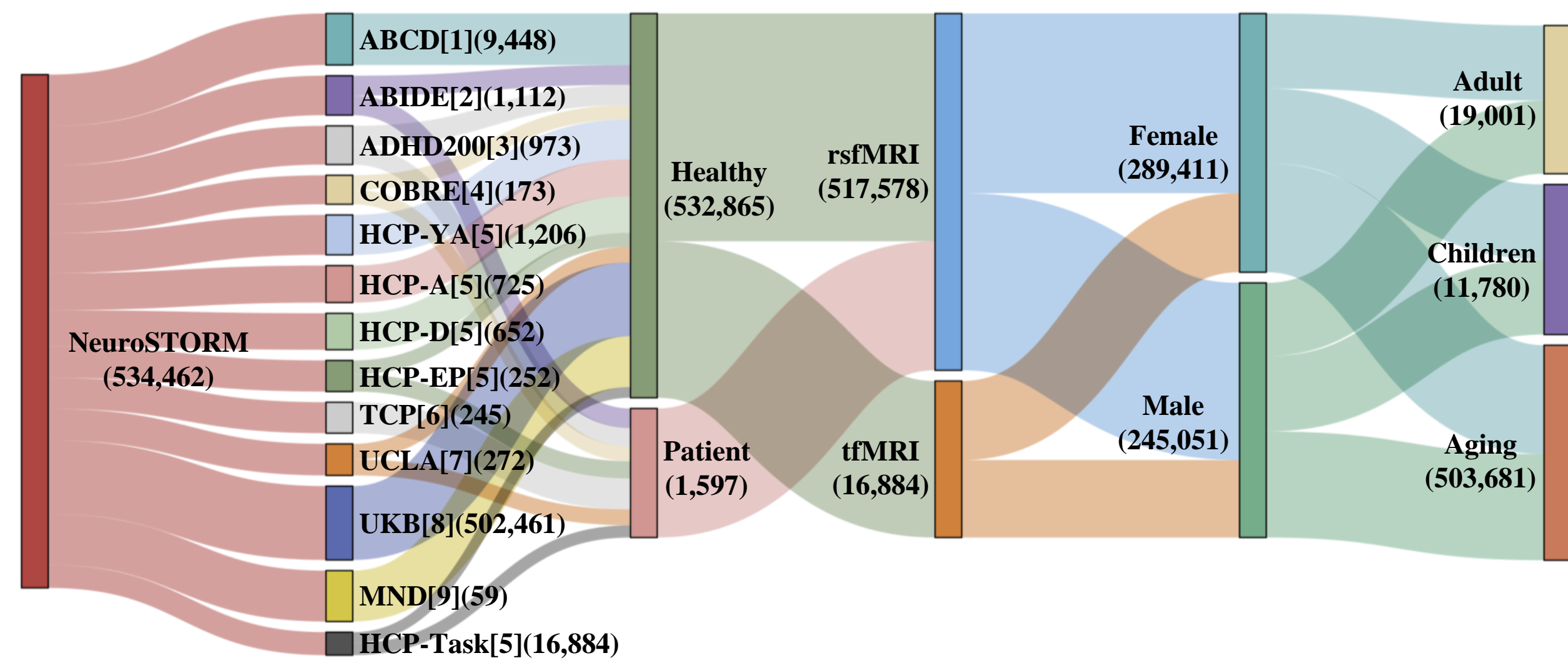
## Results

To validate the performance and applicability of NeuroSTORM, we established five benchmark datasets, each representing a distinct downstream task: a) Age/Gender prediction, b) Phenotype prediction, c) Disease diagnosis, d) fMRI retrieval, and e) task fMRI state classification.



## Dataset Corpus

The model is pre-trained on a collection of publicly available datasets, including over 500,000 rsfMRI and 16,000 tfMRI sequences. All data are aligned to 2mm MNI152 space to create standardized 4D volumes



## Conclusion

- Our study addresses two fundamental challenges in fMRI research through systematic innovations in data curation, architecture design, and benchmarking;
- NeuroSTORM exhibits satisfied performance across all tasks, highlighting the potential of the fMRI foundation model;
- NeuroSTORM creates new opportunities for integrating fundamental brain theories

## Reference

- [1] Casey, Betty Jo, et al. "The adolescent brain cognitive development (ABCD) study: imaging acquisition across 21 sites."
- [2] Craddock, Cameron, et al. "The neuro bureau preprocessing initiative: open sharing of preprocessed neuroimaging data and derivatives."
- [3] Brown, Matthew RG, et al. "ADHD-200 Global Competition: diagnosing ADHD using personal characteristic data can outperform resting state fMRI measurements."
- [4] Calhoun, Vince D., et al. "Exploring the psychosis functional connectome: aberrant intrinsic networks in schizophrenia and bipolar disorder."
- [5] Van Essen, David C., et al. "The WU-Minn human connectome project: an overview."
- [6] Chopra, Sidhant, et al. "The Transdiagnostic Connectome Project: a richly phenotyped open dataset for advancing the study of brain-behavior relationships in psychiatry."
- [7] Poldrack, Russell A., et al. "A phenome-wide examination of neural and cognitive function."
- [8] Chang, Jeryn, et al. "An fMRI dataset for appetite neural correlates in people living with Motor Neuron Disease."
- [9] Littlejohns, Thomas J., et al. "The UK Biobank imaging enhancement of 100,000 participants: rationale, data collection, management and future directions."