CLINICAL SCORES PREDICRTION AND MEDICATION ADJUSTMENT FOR PARKINSON'S DISEASE

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INTRODUCTION

Parkinson's Disease (PD) is the second most prevalent neurodegenerative disorder worldwide, characterized by progressive motor and non-motor symptoms[1]. Unfortunately, there are no definitive PD modifying therapies, so accurate course prediction in advance and appropriate medical adjustment are essential to slow down degenerative process from onset[2]. **This work addresses a novel challenge in PD course prediction specifically at month 60 (m60) of both motor and non-motor indicator utilizing Magnetic Resonance Imaging (MRI) and demographic data of previous years.**

AIM

Given a specific PD patient n, UD^n and MC^n at m60 are predicted utilizing data including MRI M_t^n, age A_t^n, motor symptomsO_t^n, medication type T_t^n and dose D_t^n with year t from onset (baseline/bl) to month 48 (m48), presenting as a mapping function f

$$f: \sum_t E_t \rightarrow Y_{m60}.$$

METHOD

Backbone for Serial MRIs

Basic 3D ResNet18 is utilized as the backbone intersperse with 3D extensional BAM (Bottle Attention Module[3]) for time series attention and SAM (Shuffle Attention Module[4]) for disrupting spatial channels.

Generative Decoder

MRI serial features concatenates with motor and mediaction feature. Composite features are padded with zeros on total feature dimension, not just in time dimension for better fusion and modality effectiveness.

$$X_{dc} = \mathrm{Concat}(X_{ec}, 0) \in \mathbb{R}^{N,(T+t)\times H,1}$$

For calculation reduction, only top-u query will be employed in the first attention layer.

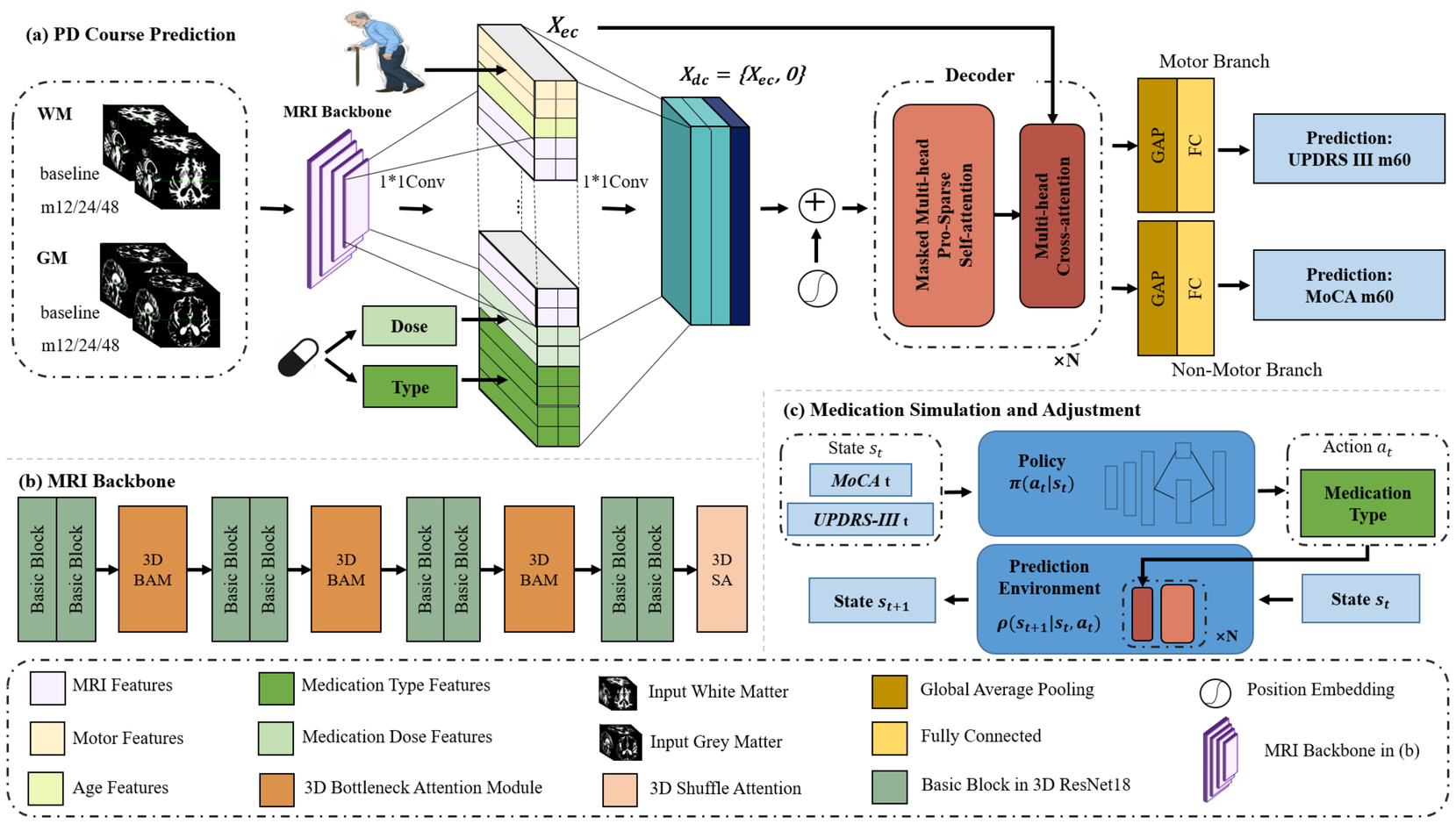

Fig. 1 The framework of our proposed method. (a) Parkinson's Disease Course Prediction network with image and non-image data. (b) MRI backbone combined with 3D ResNet18, 3D BAM and 3D SA. (C) Medication adjustment network with Dueling Double Deep Q-Network.

Medication Adjustment Module

Employing $UD_t^n$and MC_t^n for subjects **n** at timestep **t** as state vector S_t in the Markov Decision Processes (MDP). Discrete action space A with five type medications. Reward R is calculated by the change of state. Dueling Double Deep Q Network is applied to stimulate medication usage policy and decoder with same structure in prediction network is utilized for course continuation.

RESULTS

Table 1. Results for MoCA and UPDRS-III values in m60

Modal	Series	Indicator	RMSE	MAE	CC
MRI Medication	bl+ m12	MoCA	1.434 ± 0.1848	1.241 ± 0.1848	0.7578
		UP-III	5.866 ± 1.599	4.430 ± 1.254	0.1982
	bl+ m24	MoCA	1.804 ± 0.2236	1.564 ± 0.2149	0.6715
		UP-III	4.051 ± 0.4346	3.225 ± 0.4256	0.3344
	bl+ m48	MoCA	1.370 ± 0.2737	1.159 ± 0.2149	0.8409
		UP-III	3.806± 0.4346	3.200 ± 0.425	0.4529
MRI Non-image Medication	bl+ m12	MoCA	1.308 ± 0.1441	1.059 ± 0.1776	0.8278
		UP-III	5.638 ± 1.245	4.421 ± 0.9830	0.3149
	bl+ m24	MoCA	1.398 ± 0.1314	1.200 ± 0.1198	0.7954
		UP-III	**3.764 ± 0.4042**	**3.159 ± 0.4240**	**0.5282**
	bl+ m48	MoCA	**1.246 ± 0.2835**	**1.052 ± 0.2687**	**0.8586**
		UP-III	4.220 ± 0.1580	3.540 ± 0.3900	0.3663

* UP-III: UPDRS-III bl: baseline, m12: month 12 (same as m24,m48)

Table 2. Comparisons with other course prediction methods.

Ref	Modal	Subject Number	Time Step	MoCA (MAE)	UP-III (MAE)
[19]	MRI	238	BL M12 M24	2.348 1.943 1.641	- - -
[20]	MRI	213	M48	2.110	-
[21]	DAT-SPECT Clinical Data	198	M48	-	4.700
[22]	DAT-SPECT	198	M48	-	4.330
[22]	DAT-SPECT Age UP-III Gene	198	M48	-	3.220
Ours	MRI	107	M60	**1.159**	**3.200**
Ours	Medication Age MRI Motor	107	M60	**1.052**	**3.159**

*DAT-SPECT: Dopamine-transporter spectrum

CONCLUSIONS

We propose a method to predict PD course based on MRI, motor and medications features. Medication simulation with course prediction based on RL is carried out for better adaptation to individuals, which corroborate with former prediction network but need for continuous improvement.

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