

Enhancing Gait Video Analysis in Neurodegenerative Diseases by Knowledge Augmentation in Vision Language Model



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Introduction

- Neurodegenerative diseases are a common cause of morbidity and cognitive impairment in older adults, with gait impairment being one of the motor symptoms.
- Our study concentrates on video-based pathological gait analysis using a limited set of clinical recordings, facilitating cost-effective monitoring and remote surveillance.

Knowledge-based Textual Prompts

- $Desc_i$ is generated using ChatGPT-4, then refined by a neurologist.
- Based on **Knowledge-Aware Prompt Tuning** [2], learnable prompt $\{C_i^k\}_{i=1,\dots,N_{cls}} = Proj_\phi^k(RoBERTa(\{Desc_i\})) + \{X_i^k\}$, $k = 1, \dots, 8$. $Desc_i$ is distilled using RoBERTa pre-trained with unified training strategy KEPLER [5], $\{X_i^k\}$ are learnable parameters.
- Keywords extracted from $Desc_i$ is utilized as $\{D_i\}$, which is not learnable.

Utilize the Visual Prompts of Vita-CLIP [6]

Experiments and Results

Our approach is validated through experiments on two gait classification tasks:

- Gait scoring:** Assess gait impairments based on MDS-UPDRS III gait score.
- Dementia subtyping:** Differentiate the diagnostic groups (healthy / Dementia with Lewy Bodies (DLB) / Alzheimer's Disease (AD)).

Classification Results of Ablation Studies:

Configurations	Gait scoring		Dem. subtyp.	
	Acc.	Fscore	Acc.	Fscore
Baseline	64.78	60.75	86.27	79.24
Baseline+KAPT	65.98	61.97	87.29	78.48
Baseline+NTE	64.44	57.64	88.26	81.34
Ours	67.76	62.59	90.08	83.86

Classification Results Compared with SOTA:

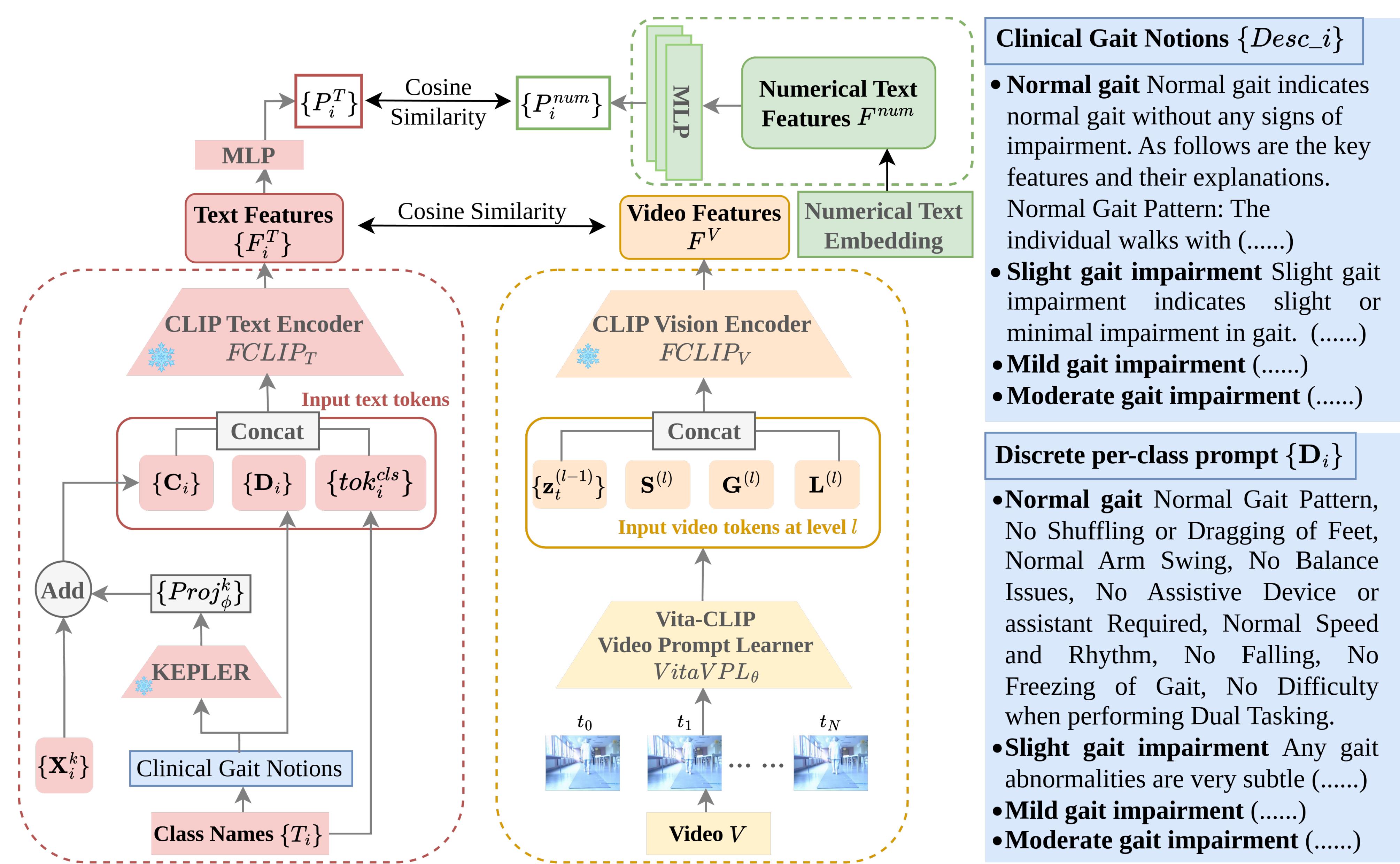
Models	Gait scoring		Dem. subtyp.	
	Acc.	Fscore	Acc.	Fscore
OF-DDNet[3]	54.73	48.59	68.92	65.38
ST-GCN [4]	49.08	43.87	61.46	56.99
KShapeNet[1]	53.69	44.85	65.27	54.86
Ours	67.76	62.59	90.08	83.86

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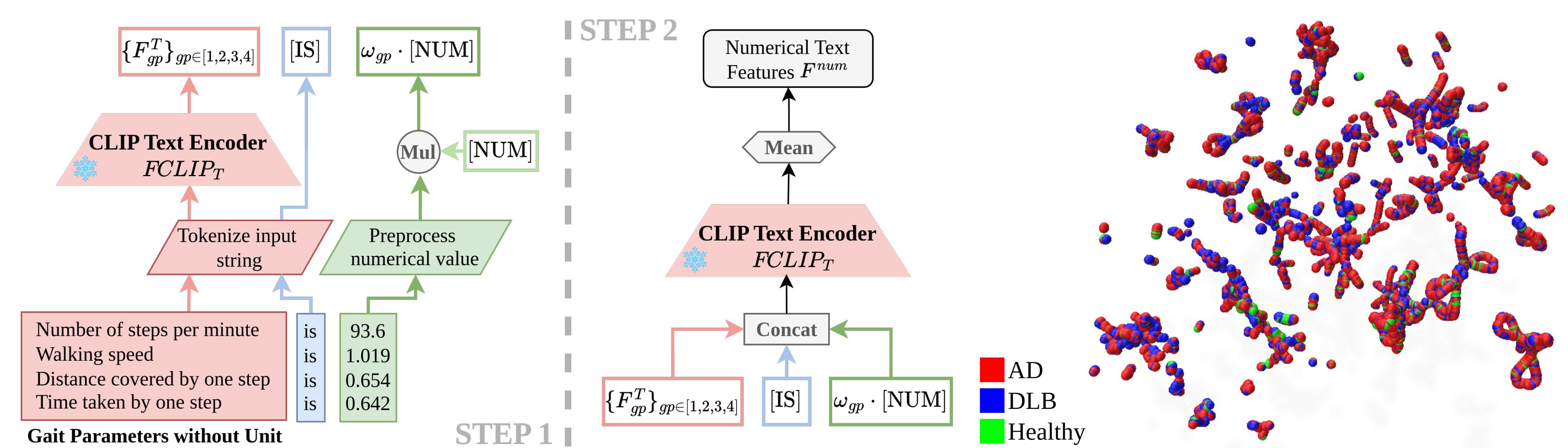
Method: Cross-modality Learning for Gait Classification Based on VLM

- We propose a knowledge augmentation strategy for diagnosing gait impairments in videos using large-scale pre-trained Vision Language Model (VLM). CLIP is utilized as backbone VLM.
- We improve visual, textual, and numerical representations learning through contrastive learning across 3 modalities: gait videos, class-specific descriptions, and numerical gait parameters.



Integrate Gait Parameters via Numerical Text Embedding (NTE)

- We employ a two-step process to embed sentences each containing 4 gait parameters.
- For numerical text embedding: $F^{num} = FCLIP_T(\{[F_{gp}^T, [IS], \omega_{gp} \cdot [NUM]]\})$, $gp \in \{1, 2, 3, 4\}$.



Interpretability: Per-class Text Feature Decoding

Idea: Decode $\{F_i^T\}$ to investigate whether the cross-modal alignment is formed through training.

- We train a 4-layer transformer decoder \mathbf{D}^T to reverse the numerical text embedding.
- Ground-truth token IDs for numerical values [num]: $tok = [\text{EOS}] + scale([\text{num}])$.
- $F_i^T \sim \hat{F}_i^T = \sum_j softmax(\frac{p_i^T \cdot p_j^{num}}{\|p_i^T\| \cdot \|p_j^{num}\|} \cdot \frac{1}{\tau}) \cdot \frac{f_j^{num}}{\|f_j^{num}\|}$, where $\tau = 0.01$ and $f_j^{num} \in \{F^{num}\}$.
- To decode $\{F_i^T\}$ into natural language descriptions: $\{\hat{Desc}_i\} = \mathbf{D}^T(\{\frac{\hat{F}_i^T}{\|\hat{F}_i^T\|}\})$.

