USE MACHINE LEARNING TO PREDICT BIOMECHANICAL GAIT PARAMETERS DURING GAIT IN PEOPLE WITH KNEE OSTEOARTHRITIS

Presented by Group 03 – 1

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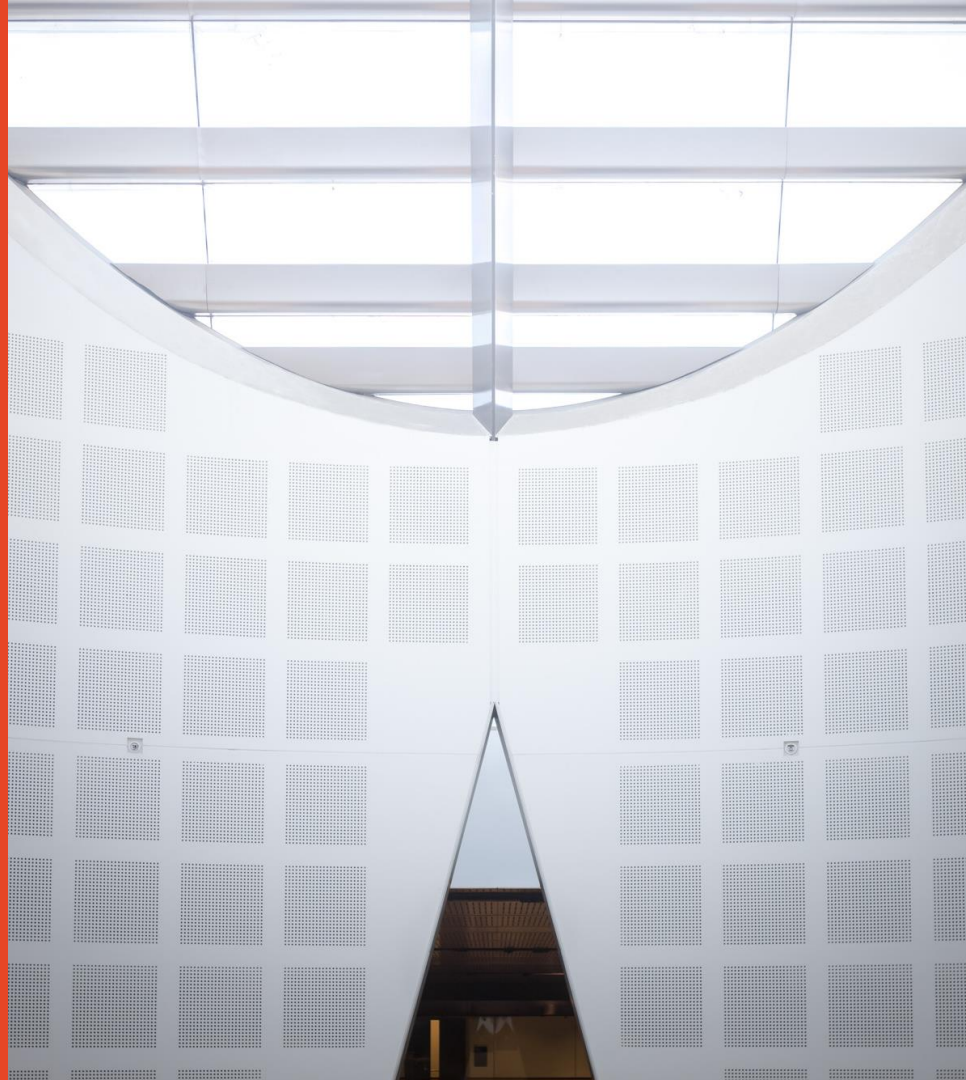


Information

- *Tonghuan Liu (tliu0082)*
  - *Motivation of the work, Related work/background study*
- *Mohan Xi (moxi0368)*
  - *Outlining of own approach/method/algorithm*
- *Weijia Chi(wchi0957)*
  - *Main result of own project*
- *Feixiang Wang(fwan0760)*
  - *Discussion/evaluation of our own work*
- *Yang Guo (yguo0583)*
  - *Discussion/evaluation of our own work*
- *Ruhao Ji (ruji6336)*
  - *Conclusion and reflection of own work*

Motivation/objective of the work

Limitations: traditional laboratory methods for measuring key indices are expensive, limiting their universal application capacity

Goal: Use deep learning and 3D marker trajectory data to predict HKA, FPA, and **KAM (focus on Peak KAM values)**

- Hip-Knee-Ankle (HKA) Angle Deviation: Reflects lower limb alignment during walking
- Foot Progression Angle (FPA): Indicates foot rotation relative to the movement direction
- Knee Adduction Moment (KAM): Measures knee joint loading; elevated KAM correlates with OA progression

Related work/background study

1. Methods for Calculating FPA and HKA

2. Advancements in KAM Prediction Using Machine Learning

- Neural Networks (Boswell et al., Rokhmanova et al.),
- RNNs (Wang et al., Palad et al.),
- CNNs (Yan et al., 2022),
- Transformers (Tan et al., 2023),
- Hybrid Models...

3. Identification of Critical Markers

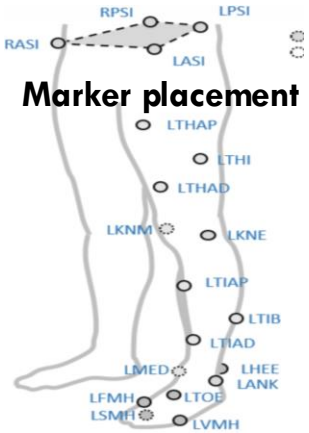
- Statistical, Machine Learning, Neural Networks...

Outlining of own approach/method/algorithm

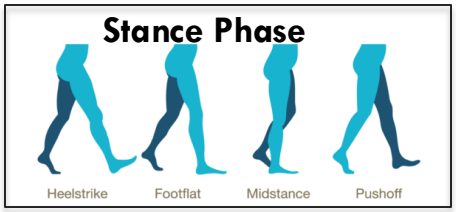
Data:

2,920 trajectory files

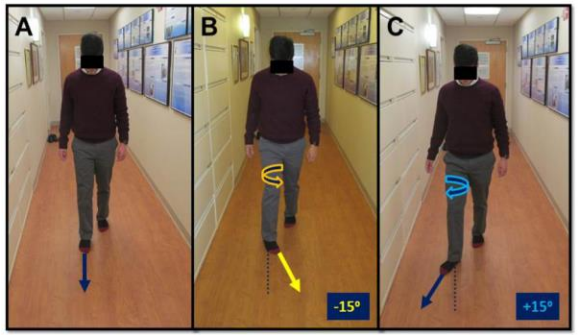
2,920 model output files



Marker placement



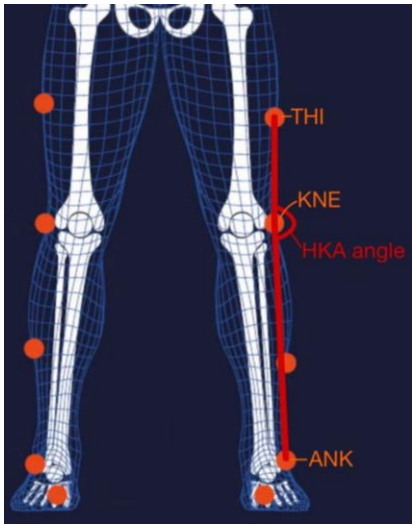
For FPA:



$$\mathrm{FPA}_{\mathrm{avg}} = \frac{1}{n} \sum_{t=t_{15\%}}^{t_{50\%}} \mathrm{FPA}(t)$$

where t_{15}% and t_{50}% denote the time points corresponding to 15% and 50% of the stance phase, respectively, and n is the number of time frames within this interval.

For HKA angle deviation:

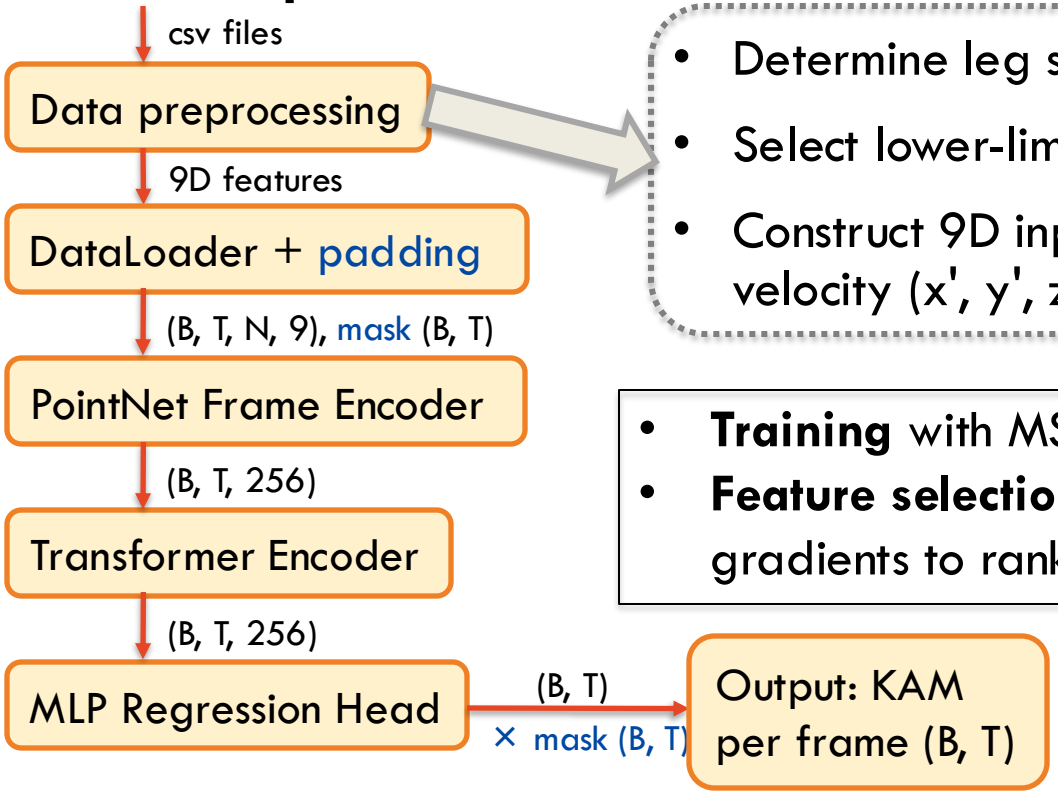


$$\mathrm{HKA}_{\mathrm{dev}} = \max_{t} \left(\theta_{\mathrm{HKA}}(t)\right) - \theta_{\mathrm{HKA}}(t_0)$$

where $\mathrm{HKA}_{(}\mathrm{dev}_{)}$ is the change in HKA angle during the stance phase, computed as the difference between the maximum value and the initial value at the first frame t_0.

Outlining of own approach/method/algorithm

For KAM prediction:



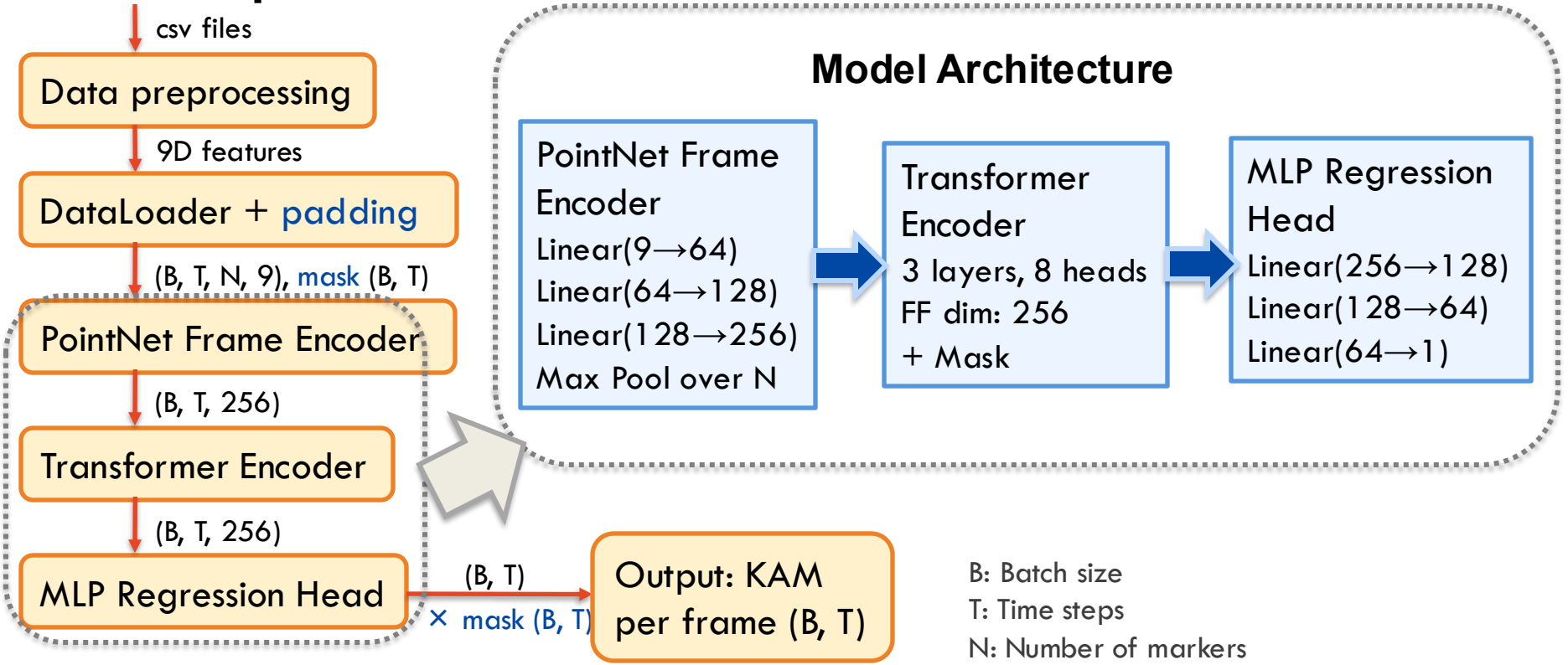
- Determine leg side (L/R)
- Select lower-limb markers
- Construct 9D input features: position (x, y, z) + velocity (x', y', z') + acceleration (x", y", z")

- **Training** with MSE loss on valid (non-masked) frames.
- **Feature selection**: Saliency-based analysis using gradients to rank marker importance

B: Batch size
T: Time steps
N: Number of markers
FF dim: Feedforward dimension

Outlining of own approach/method/algorithm

For KAM prediction:



B: Batch size
T: Time steps
N: Number of markers
FF dim: Feedforward dimension

Main results of own project

1. Automated HKA and FPA Calculation Script

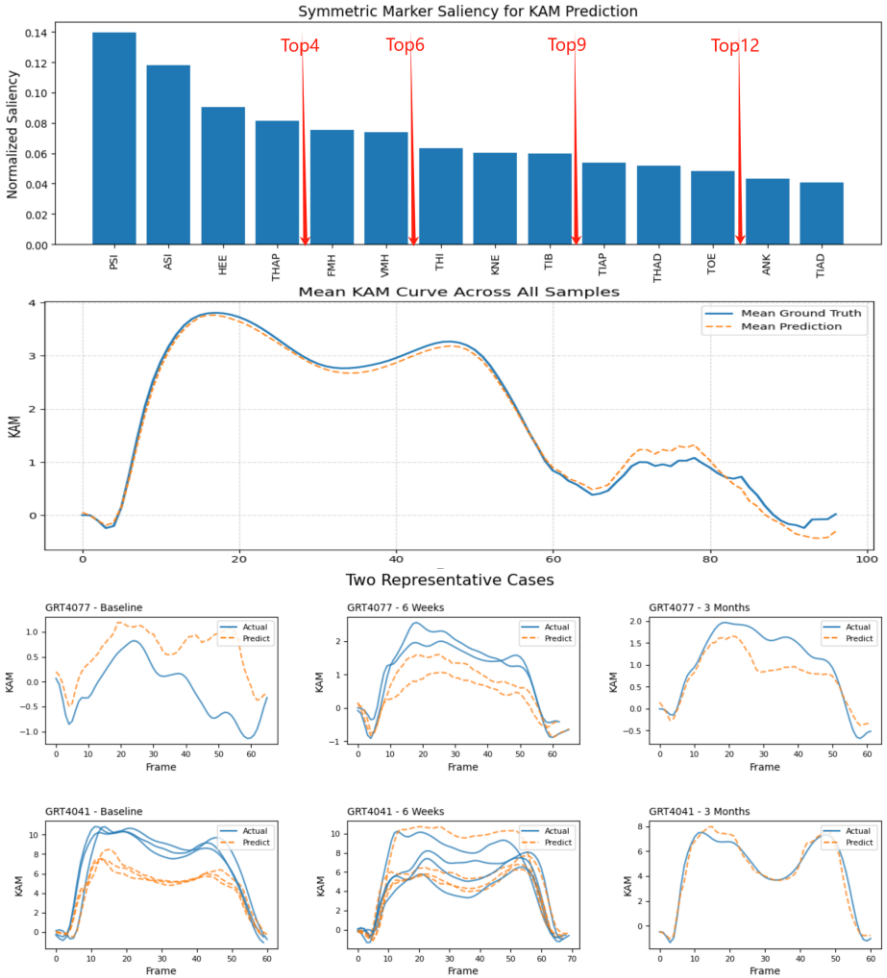
2. Feature saliency ranking

3. Model Accuracy

- Test MSE: 0.40
- Peak 1,2 MSE: 0.55, 0.46

4. Model stability check:

- The consistency of prediction error trends across timepoints within individuals
- Peak1,2: 59%, 56%



Discussion/Evaluation of own work

Extra Information:

Sample code:

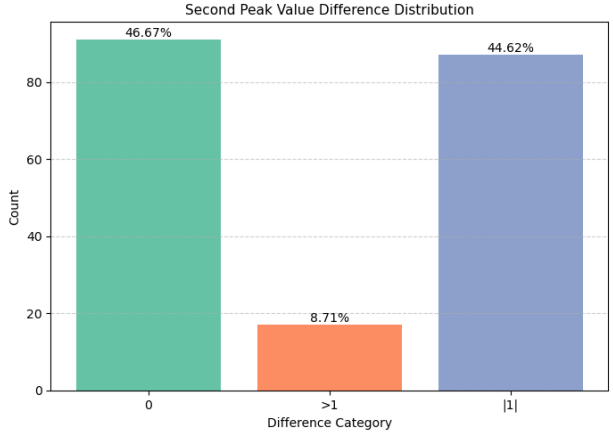
Participant_ID+Time_Point+Walk_Step+Test_Time(10006week_walk01_l1)

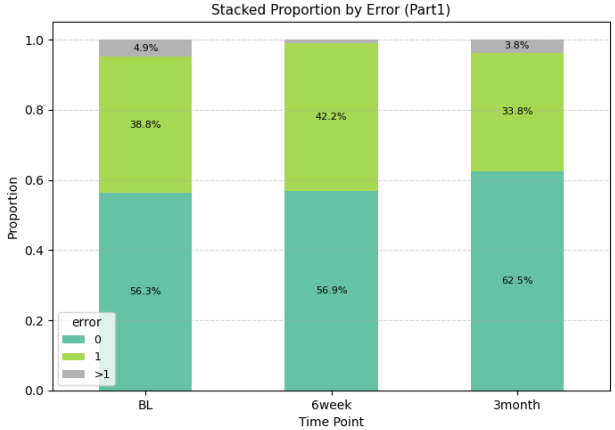
Error Calculation Formula:

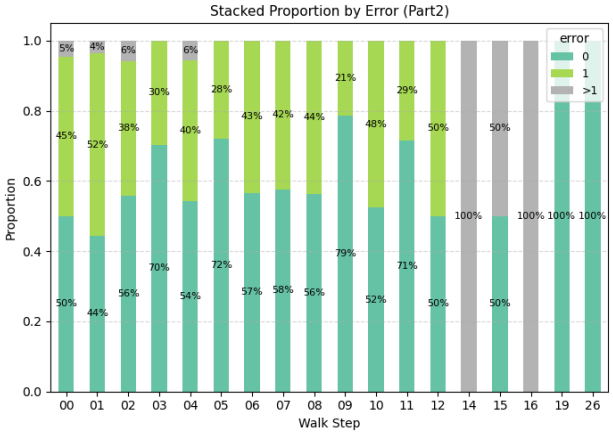
ABS(Floor(True Peak value)-Floor(Actual Peak Value))

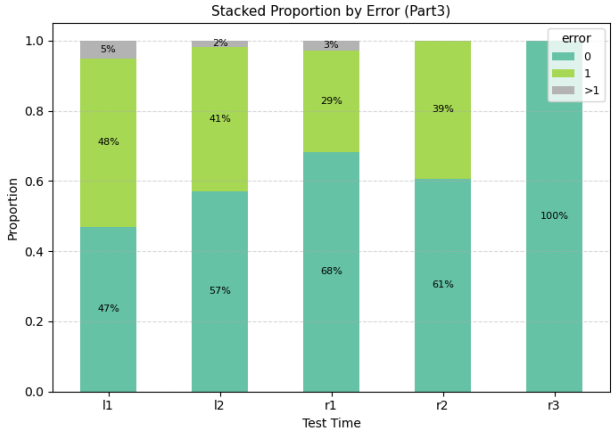
Value_difference:

Error in 6week – error in Baseline for the same participant_ID









Discussion/Evaluation of own work

Limitations

- The prediction errors of the same participant at different test time points vary greatly.
- The clinical interpretation and verification of the prediction results are still insufficient.
- 2D data has the potential as a low-cost alternative.
- The current model mainly focuses on spatio-temporal feature modeling.

Conclusion and reflection of own work

Key Achievements

- Accurate Peak KAM Prediction
- Interpretability Enhancement / Cost-Effective Alternative

Reflection and Future Directions

- Multimodal Attribution Framework
- Dynamic Adaptation Strategies
- Robustness Enhancement
- Clinical Validation