Using Learnable Physics for Real-Time Exercise Form Recommendations

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Motivation

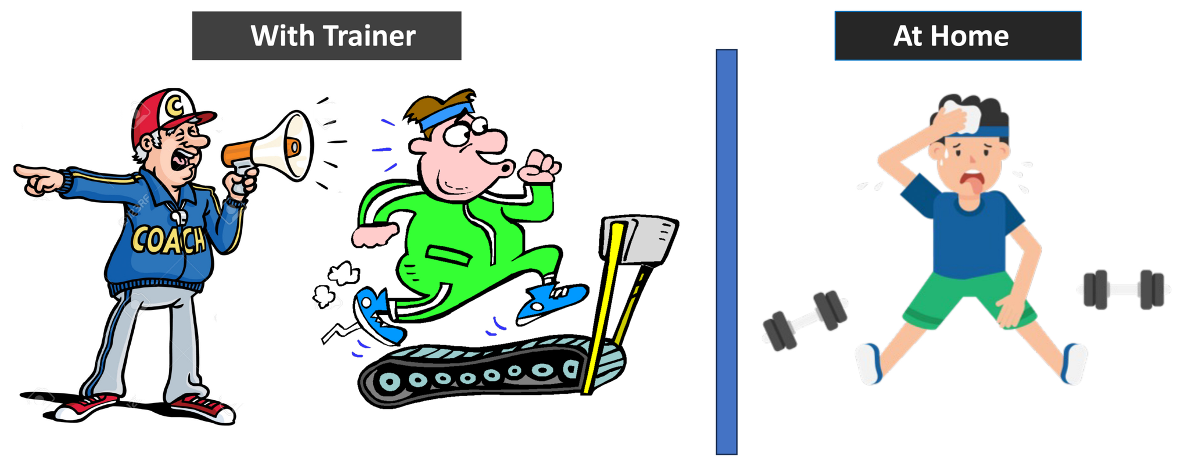

Figure 1. Workout with Trainer vs Self-Practice at Home

- Home Settings do not have adequate exercise evaluation mechanism
- Personal trainer is not always available, even in gym settings
- Rehabilitation therapies and fitness workouts can benefit from real-time evaluation systems.

Problem

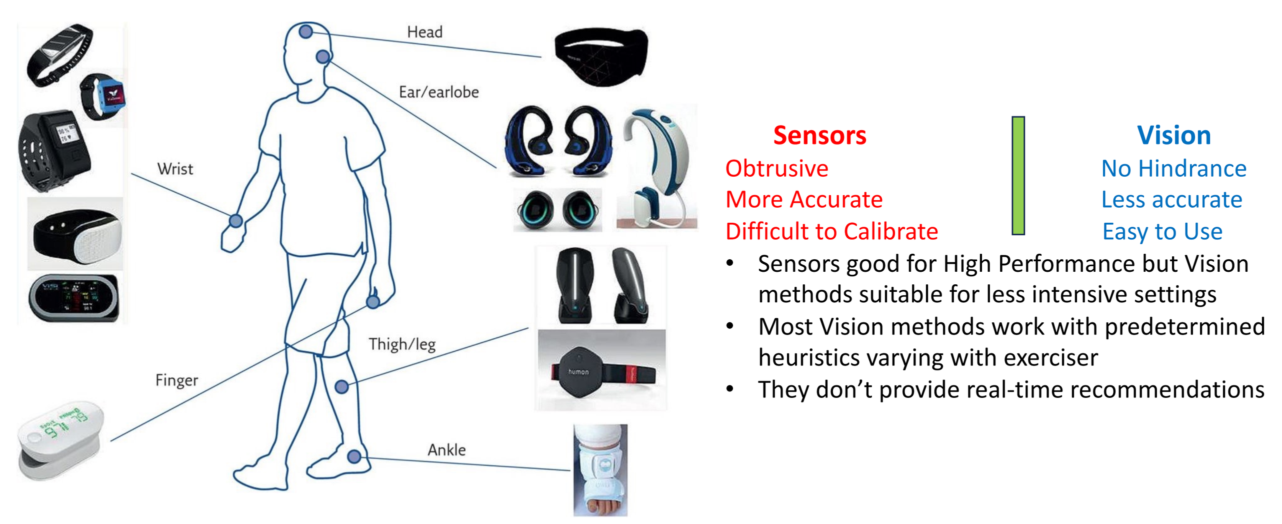

Figure 2. Example of Body worn sensors and comparison with vision based methods

Solution

- Using a base inference engine designed to learn relationships between physical objects
- Interaction Networks(IN) [1] is one such method
- Real-time Exercise form recommendation

Background - IN and its input

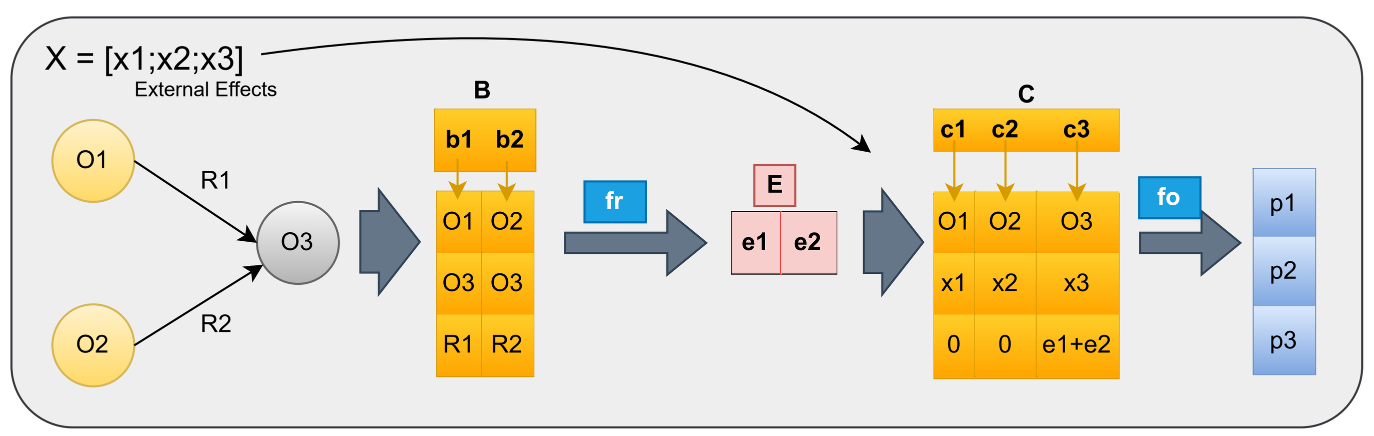

Figure 3. Example showing working of Interaction Network

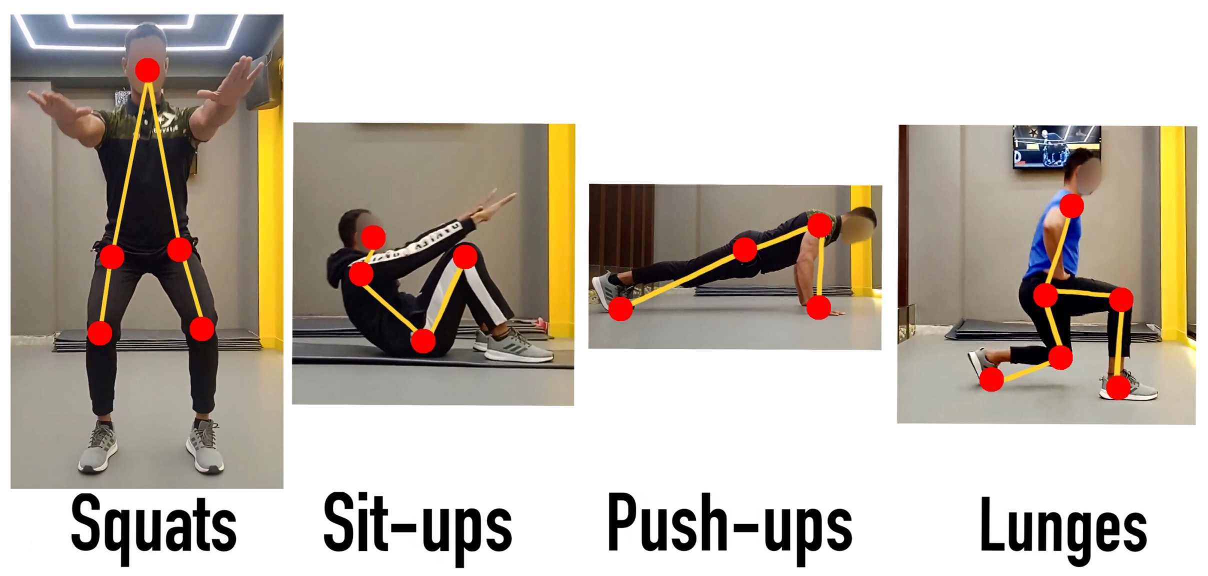

Figure 4. Stick Figure for four full-body exercises. Selected landmarks for each exercise are marked in red.

Methods

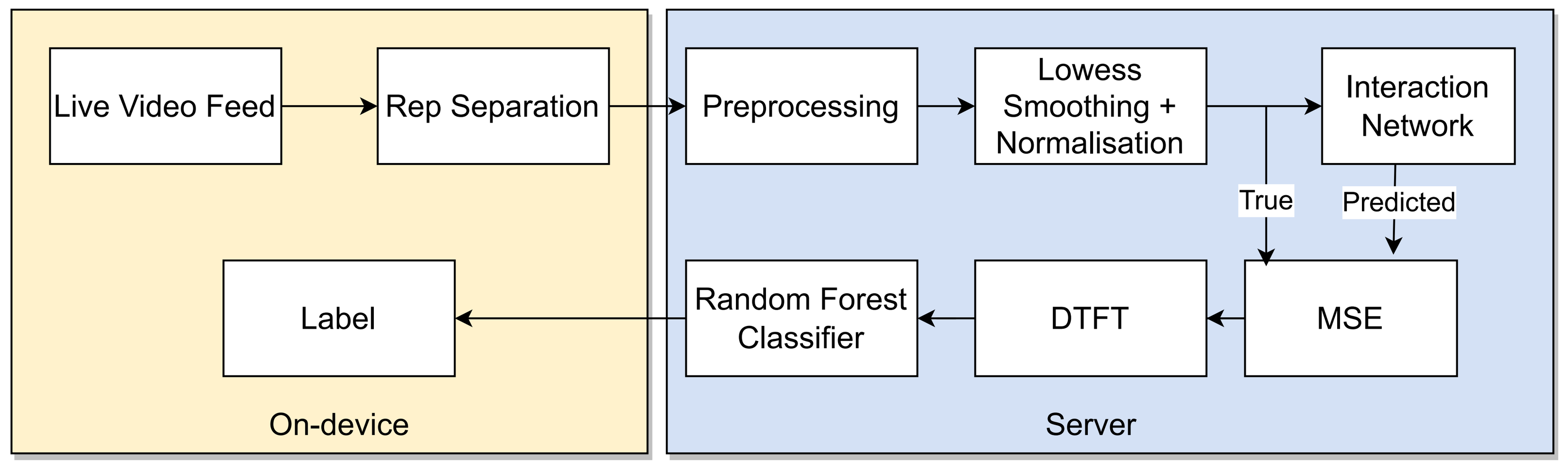

Figure 5. Flowchart illustrating our Interactive System's workflow.

- **Input:** Initial position and velocity data of the exercise Landmark
- **Output:** Dynamics rollouts as per the learned physics
- **Classification:** The MSE for each landmark converted to frequency domain
- **Recommendation:** One of the class categories

Results

Model	Squats	Pushups	Lunges	Situps
MLP	0.91±0.02	0.98±0.03	0.95±0.03	**0.99±0.01**
RNN	0.85±0.04	0.98±0.01	0.94±0.01	0.98±0.02
GRU	0.87±0.03	0.98±0.01	0.93±0.02	0.94±0.04
IN	**0.94±0.02**	**0.98±0.01**	**0.97±0.01**	0.98±0.01

Table 1. Avg. F1 scores for full body exercises

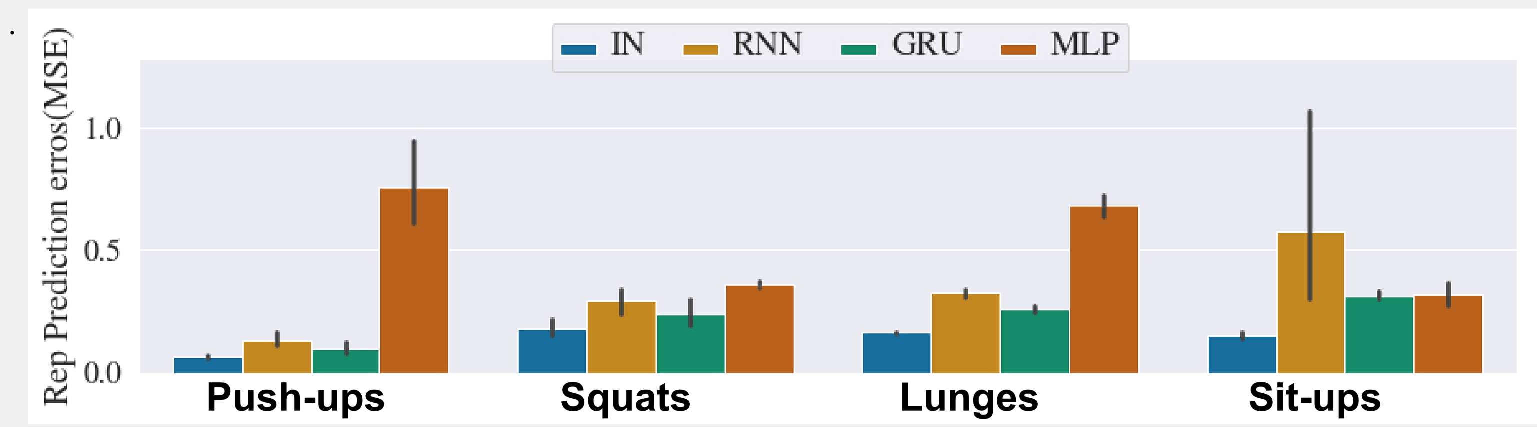

Figure 6. Avg. rollout pred. errors over exercise reps(MSE) for Baselines and IN.

Model	Shoulder Press	Front Raise
Ng[3]	0.90	0.77
Pose Trainer[2]	0.49	0.76
MLP	**0.99±0.01**	0.84±0.04
RNN	0.99±0.01	0.79±0.05
GRU	0.95±0.06	0.80±0.04
IN	0.98±0.01	**0.88±0.03**

Table 2. Avg. F1 scores for upper body exercises

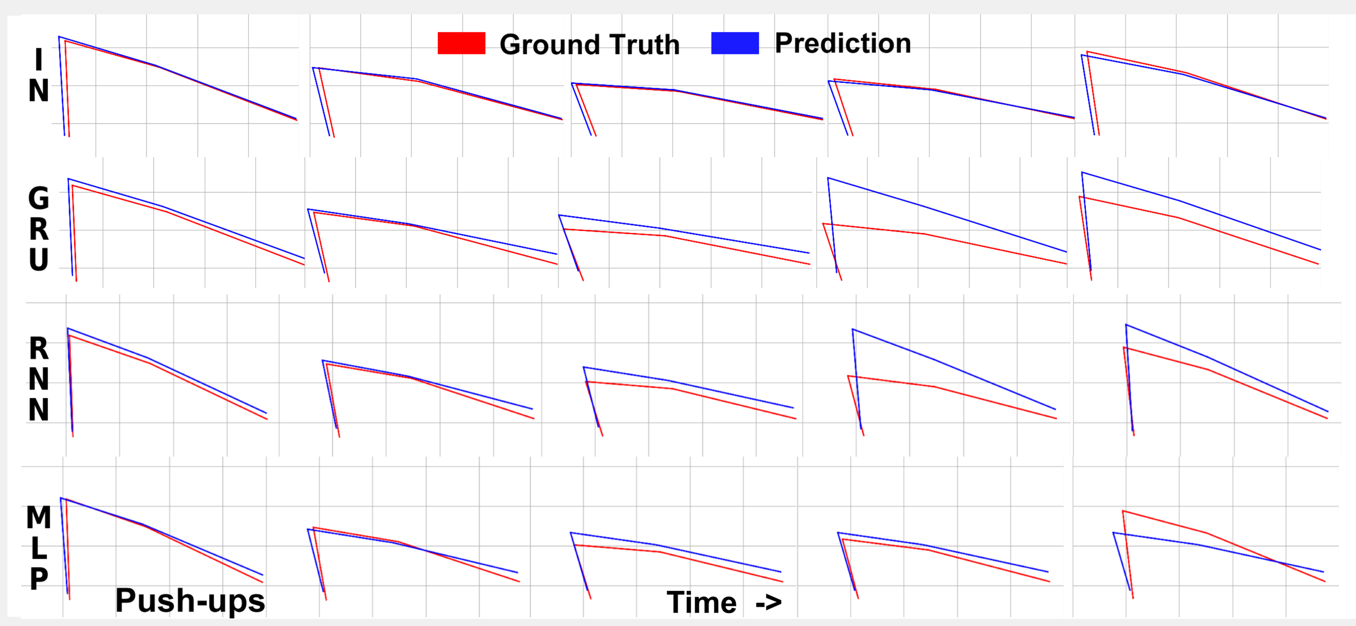

Figure 7. Pushups comparison for Baseliens

Incorrect Categories - Planks

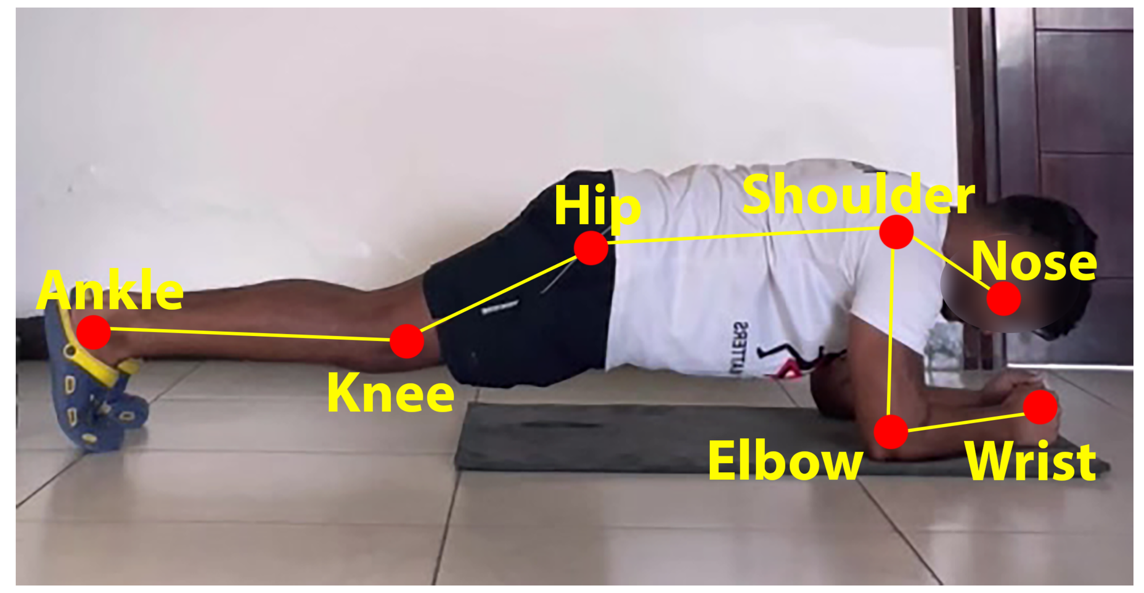

Figure 8. Planks - landmarks

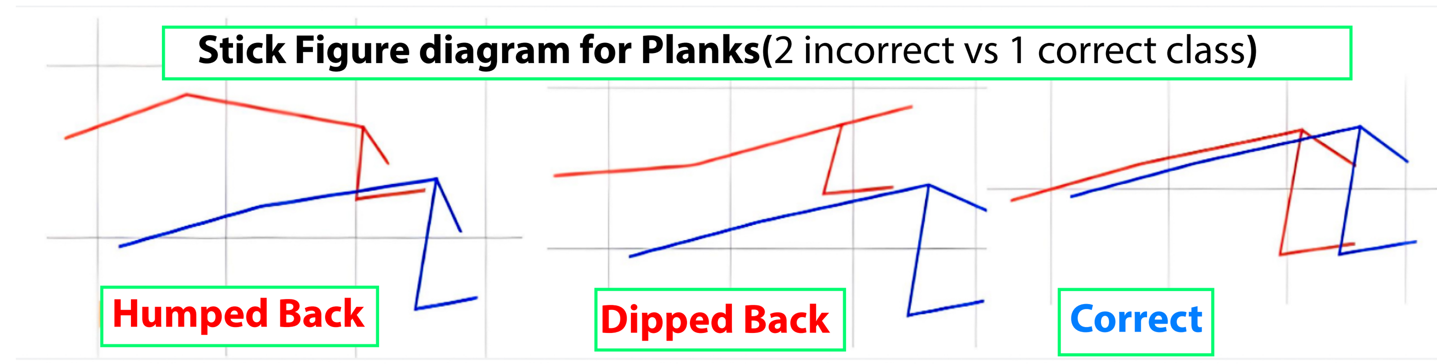

Figure 9. Planks correct incorrect classes

Real time recommendations

- **Mobile application**
  - Captures a user doing an exercise
  - Outputs the coordinates for landmarks
  - Each repetition is identified, and passed to the server
- **Server**
  - Classifies a rep as correct or diagnoses it as a mistake of a particular type
- **Corrective Recommendations**
  - Message specific to the estimated diagnosis is displayed via the app
  - At normal pace, this feedback arrives before their next rep is halfway complete

Exercise	Mean(sec)	Standard deviation(sec)
Squats	0.55	0.13
Sit-ups	0.39	0.07
Push-ups	0.36	0.11
Lunges	0.54	0.09

Table 3. Lag time(seconds) for new rep recognition.

Conclusion and Discussion

- Physics endowed pipeline is effective in predicting motion dynamics resulting in good classification performance
- Results for high rollout MSE models degrade as the number of classes increase
- Low latency prompts the user to correct any mistakes in technique without much delay

Front Raise	MLP	RNN	GRU	IN
2 Classes	0.96±0.03	0.93±0.02	0.93±0.06	**0.96±0.03**
4 Classes	0.91 ±0.03	0.90±0.01	0.89±0.05	**0.91±0.01**
6 Classes	0.82±0.04	0.79±0.05	0.80±0.04	**0.88±0.03**

Table 3. Front Raise Classification Complexity. Methods that do not model exercise dynamics show significant performance drop as the number of pred. classes increase.

References

[1] Peter Battaglia, Razvan Pascanu, Matthew Lai, Danilo Jimenez Rezende, et al. Interaction networks for learning about objects, relations and physics. *Advances in neural information processing systems*, 29, 2016.

[2] Steven Chen and Richard R Yang. Pose trainer: correcting exercise posture using pose estimation. *arXiv preprint arXiv:2006.11718*, 2020.

[3] Jiunn Ng. *Posture evaluation for variants of weight-lifting workouts recognition*. PhD thesis, UTAR, 2020.

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