Domain Knowledge-Informed Self Supervised Representations for Workout Form Assessment

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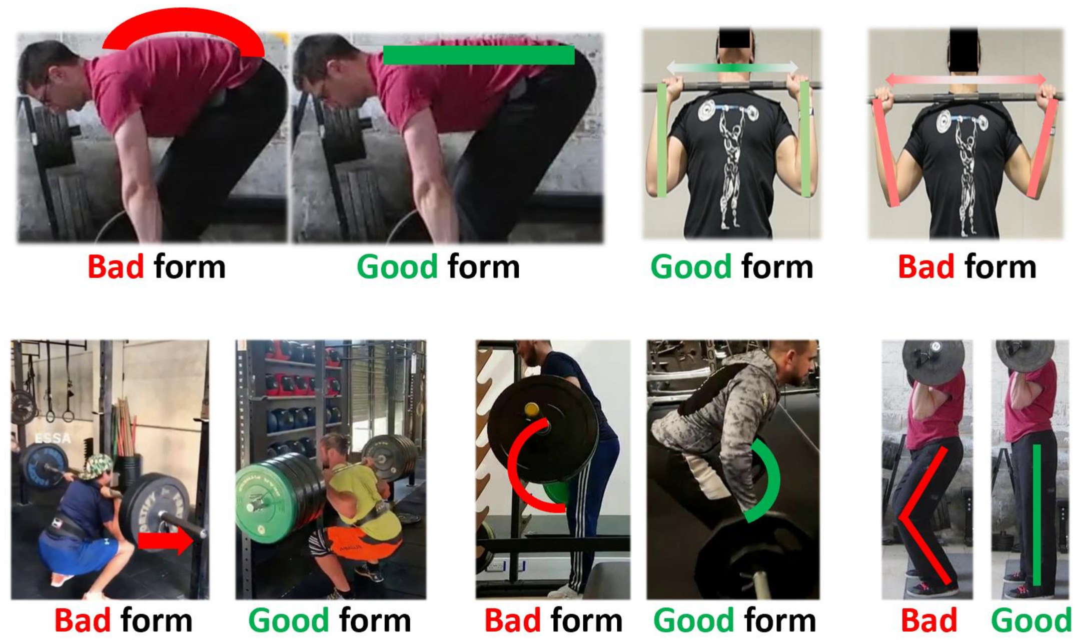
ECCV TEL AVIV 2022

Task Definition

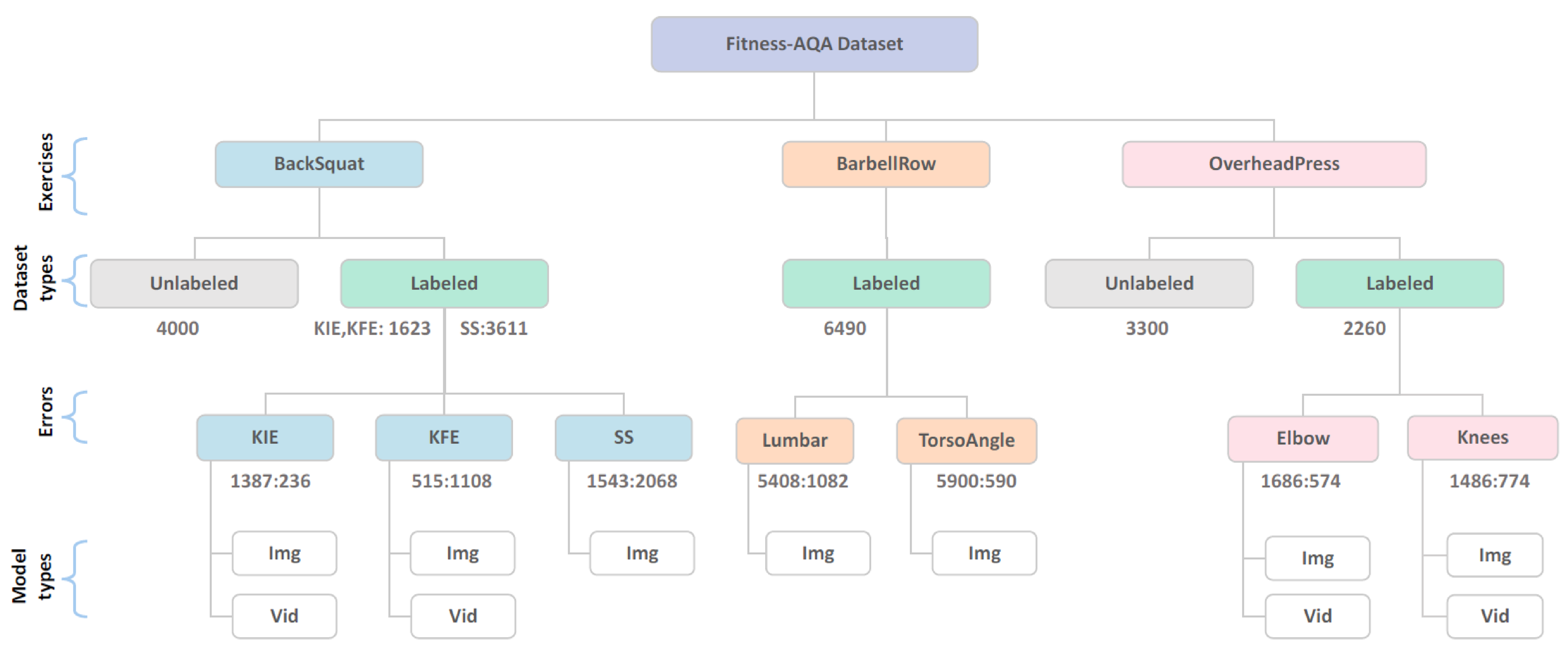
Detecting errors (Bad forms) in Workout Form in Real-World Scenarios



Shortcomings of Current Work

- Academic research is limited to controlled conditions
- Use off-the-shelf 2D/3D Pose Estimators
  - Good for simple, controlled conditions
  - But does not fare well in real-world, in-the-wild conditions
- Dataset void: No suitable in-the-wild datasets available

Contribution 1: Our Fitness-AQA Dataset



- Real-world videos
- People making errors under the impact of actual weights
- Occlusions
- Various types of clothing, background, illumination
- Unusual poses
- Severe to Subtle, Finegrained action errors

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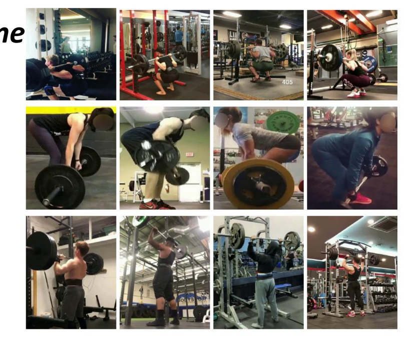
- Characteristics of exercises in the dataset:
- Compound exercises – more likely to cause injuries than isolation exercises
- Upper & Lower bodies covered
- Targeting injury prone & complex joints: shoulders, knees, hips, spine, wrists

Challenges of Fitness-AQA Dataset

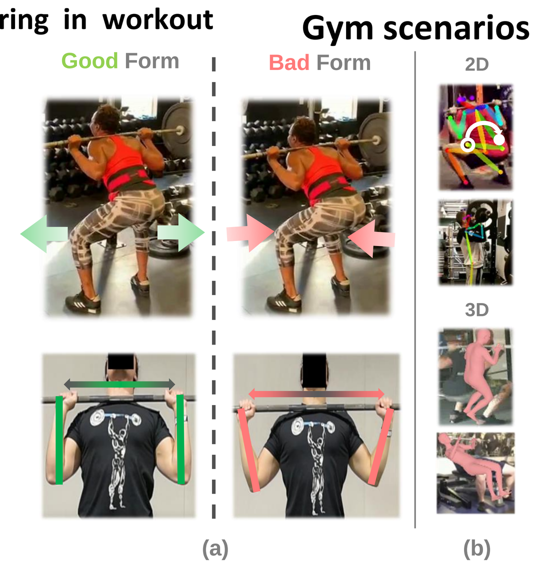
People record themselves by using their cellphone cameras placed somewhere in the vicinity

- camera angles
- occlusion from gym equipment
- illumination
- clothing



Pose estimators don't perform well

Errors of small magnitude generally occurring in workout form < Errors in pose estimation in Gym scenarios

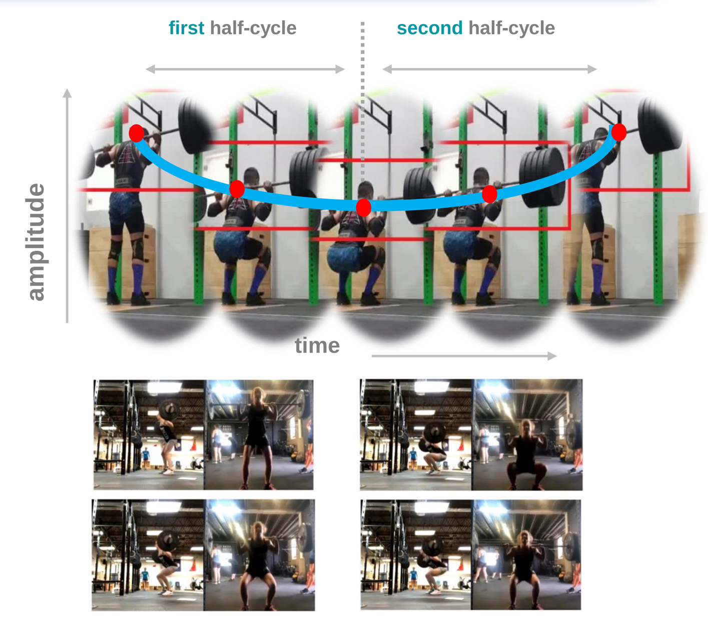


Our Proposal

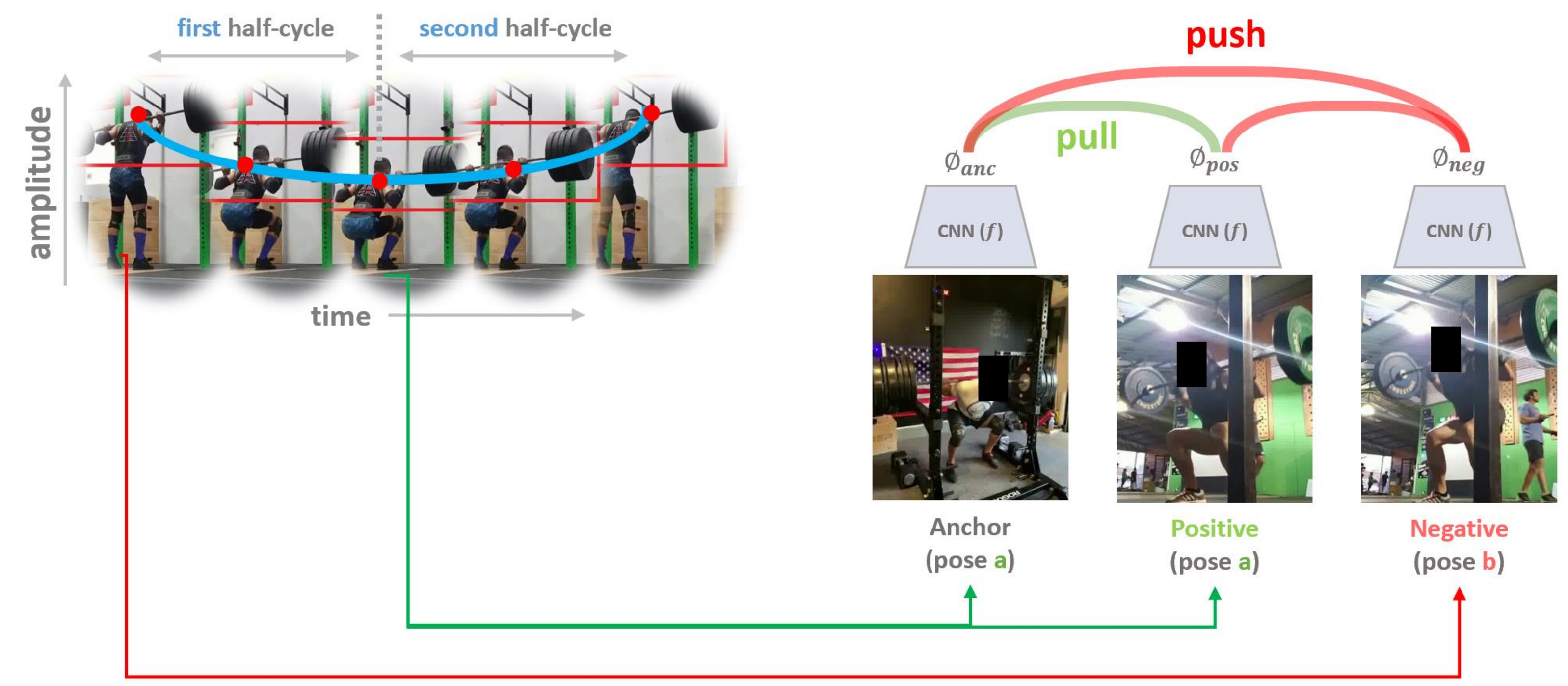
- Replace error-prone pose estimators with Self-Supervised Pose-sensitive representations learned from unlabeled real-world videos
- Map these self-supervised representations to errors-labels using smaller labeled datasets

Contribution 2: Quasi-Synchronizing Videos

- Steps to Quasi-synchronize videos:
- Track the weight to get trajectories along the time direction
- Normalize the amplitudes of these trajectories
- At any given amplitude, the people doing the same exercise would approximately be in the same pose

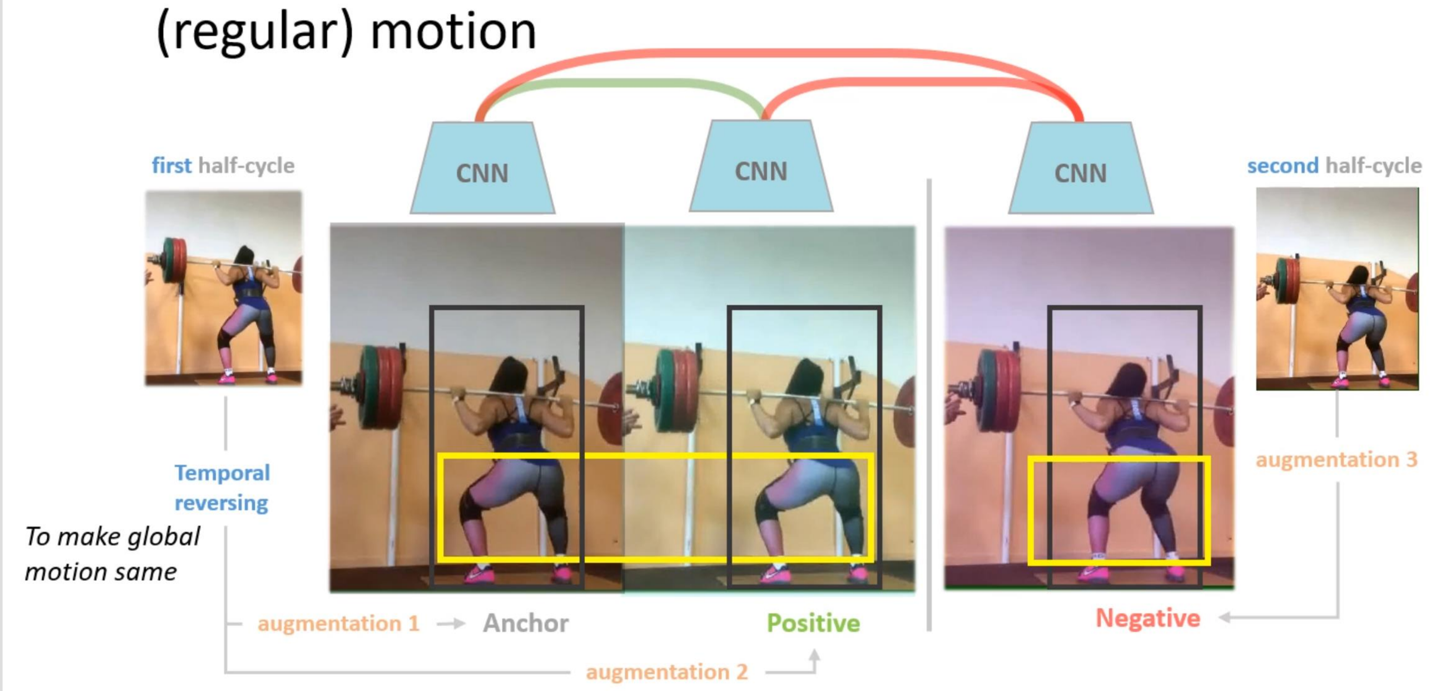


Contribution 3: Self-Supervised Pose Contrastive Learning



Contribution 3: Self-Supervised Motion Disentangling

- Objective: Separate local (irregular/erroneous) motion from global (regular) motion



People generally make errors when lifting the weight, as opposed to lowering them

We leverage this asymmetricity

Exp. 1 — Simple Conditions

Features Extraction	Accuracies (%)					
	KIE	CVRB	CCRB	SS	KFE	Avg.
HMR-TDM [21]	89.80	**98.65**	93.05	**87.30**	83.58	89.08
Ours CVCSPC	**95.92**	91.89	**94.44**	77.77	**89.55**	**89.92**

Exp. 3 — OHP

Feature extraction model	Modality	F-score ↑	
		Elbow Err.	Knees Err.
OpenPose-TDM [2,27]	2D Pose	0.4265	0.7131
SimSiam [5]	Image	0.4145	0.5301
Ours CVCSPC	Image	0.4522	0.7203
TemporalXform [17]	Video	0.4138	0.8416
Ours MD	Video	**0.4552**	**0.8452**

Exp. 4 — Xfer Repr.

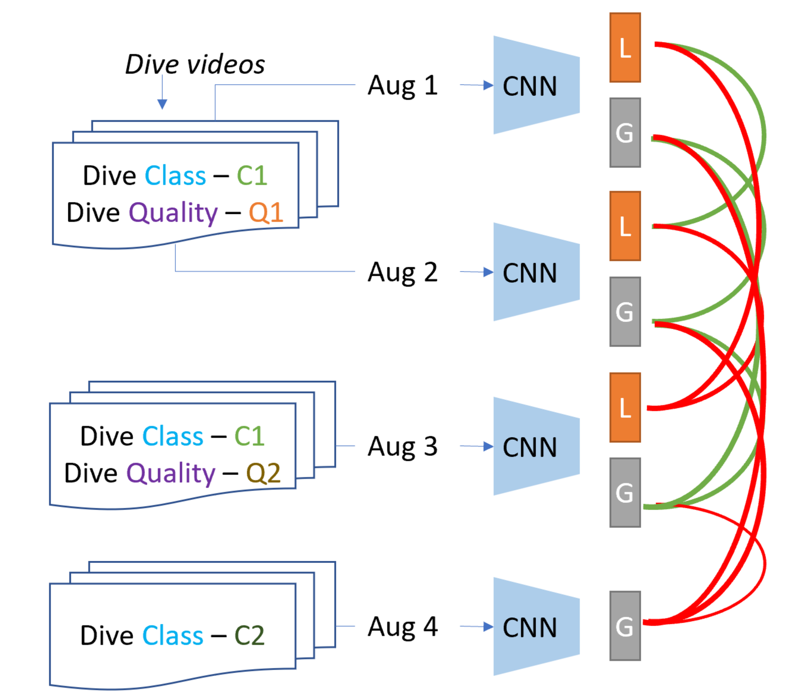
Feature extraction model	Modality	F-score ↑	
		Lumbar Err.	Torso Err.
OpenPose-TDM [2,27] (SQ→BR)	2D Pose	0.5422	0.4060
SimSiam [5] (SQ→BR)	Image	0.5934	0.4543
Ours CVCSPC (SQ→BR)	Image	**0.6057**	**0.4800**
Ours CVCSPC (OHP→BR)	Image	0.5760	0.4675
Ours CVCSPC (SQ+OHP→BR)	Image	**0.6338**	**0.5261**

Pose Retrieval Exp.

Exp. 2 — Complex Conditions

Feature extraction model	Modality	F-score ↑	
		KIE	KFE
OpenPose-TDM [2,27]	2D Pose	0.4143	0.8123
OpenPose-TDM* [2,27]	2D Pose	0.3186	0.7968
SPIN-TDM [22,27]	3D Pose	0.2878	0.7761
ImageNet [39]	Image	0.1923	0.7725
SimSiam [5]	Image	0.2270	0.7868
Ours PAD	Image	0.3180	0.7784
Ours Vanilla PC	Image	0.4118	0.7965
Ours CVCSPC	Image	**0.5195**	0.8286
Kinetics [20]	Video	0.2970	0.8184
VideoSpeed-1 [1]	Video	0.3095	0.8155
VideoSpeed-2	Video	0.3617	0.8000
VideoRot [18]	Video	0.3333	0.8138
TemporalXform [17]	Video	0.3414	0.8319
Ours TemporalXform-1	Video	0.3457	0.8097
Ours TemporalXform-2	Video	0.2286	0.8184
Ours MD	Video	0.4186	**0.8338**
Ours MD + CVCSPC	Image, Video	**0.5263**	**0.8468**

Motion Disentangling for Scoring Olympic Dives



Model	SSL SoTA [38]	Ours baseline	Ours MD
Sp. Corr.	0.7700	0.5665	**0.7763**