

APPENDIX

CARE: Counterfactual-based Algorithmic Recourse for Explainable Pose Correction

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In this appendix, we include details that we could not include in the main paper owing to space constraints. In particular, we include the following additional information:

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A1. Sample Dataset Images

In the main paper, we showed our experimental results on three datasets: ASL, Yoga-20, and Pilates. Figures A1, A2 and A4 show sample images from the different classes in each of these dataset. In Figure A3, we show the keypoints that we use for gesture recognition on the ASL dataset.

A2. On Enforcing Sparsity in CARE’s Counterfactuals

We follow [18] and integrate a post-hoc operation on the obtained corrected pose $p_{corrected}$, where each angle in the corrected pose is greedily restored back to the corresponding value in the input incorrect pose (p_{inc}). To decide whether to restore an angle $p_{corrected}^i$ to the value p_{inc}^i , we check if the difference between these two values is less than a predefined threshold T . After a value is restored, we check if this operation has caused the pose class to change. Since we do not want the pose class to deviate from the cor-

rect pose class, we undo the last operation and return the corrected pose.

A3. More Qualitative Results

In this appendix, we also include additional qualitative results for the Yoga dataset, where we show the ground truth pose, incorrect pose and the generated counterfactual pose. We show these results for 6 poses - Lord of the Dance (Figure A5), Warrior3 (Figure A6, Bow (Figure A7, Camel (Figure A8), Boat (Figure A9) and Side Plank (Figure A10). The angle values for these poses are given in Table A1.

A4. Additional Ablation Studies

Varying the proximity weight: While generating counterfactuals using the counterfactual generator, proximity weight is one of the tunable hyperparameters. While we use the default value of 0.5 in our main experiments, we performed a study to observe the effect of changing the proximity weight in the pose correction performance. Note that a higher proximity weight signifies that the generated counterfactual poses will be closer to the incorrect pose. In contrast, a low proximity weight allows the counterfactuals to be far from the incorrect pose. In Table A2, we observe that in all three datasets, no clear trend is discerned in the pose correction performance when the proximity weight is increased. At higher thresholds, the effect of proximity weight is almost negligible. One possible explanation of this is that in our CARE pipeline, instead of directly generating and selecting one counterfactual, we generate multiple counterfactuals and pick the corrected pose to be the counterfactual which is closest to the incorrect pose.

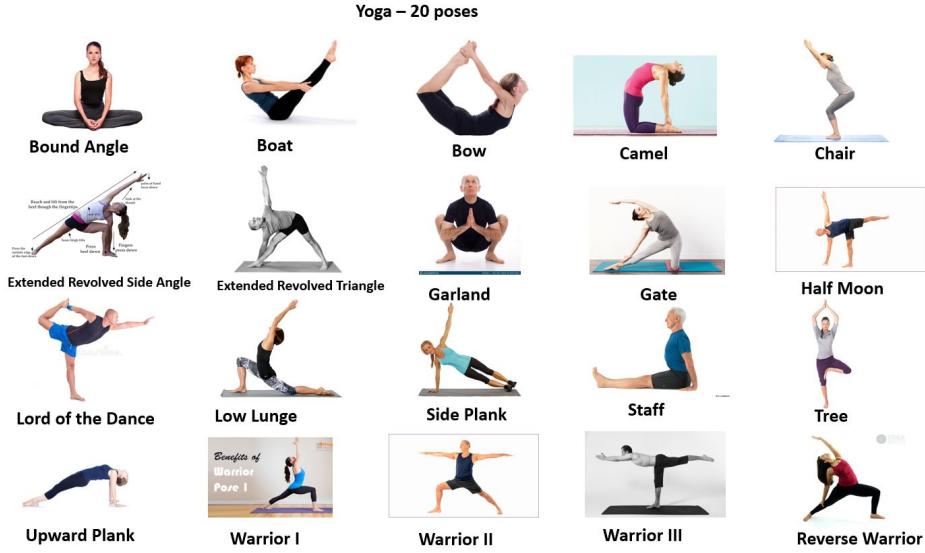


Figure A1. **Yoga-20 Dataset:** Sample images of each of the 20 poses in the Yoga dataset.

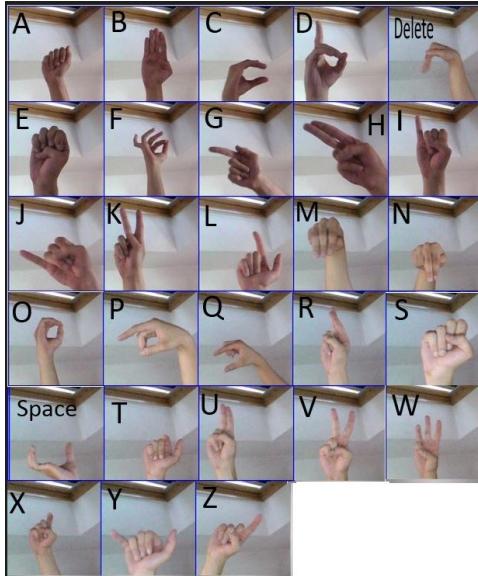


Figure A2. **ASL dataset:** Figure shows the gestures for letters A to Z, delete and space.

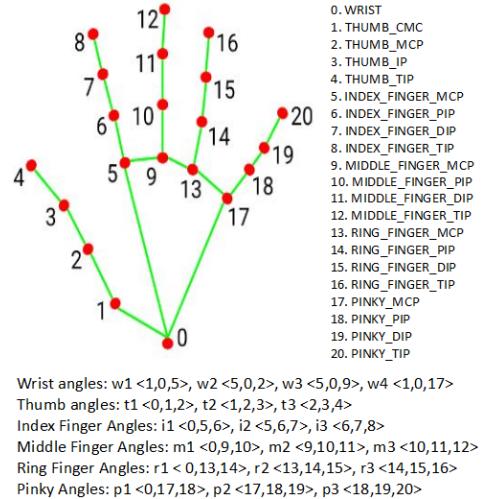


Figure A3. **Hand Landmarks for ASL dataset:** Figure shows the keypoints for hand gesture recognition.

Pilates-32

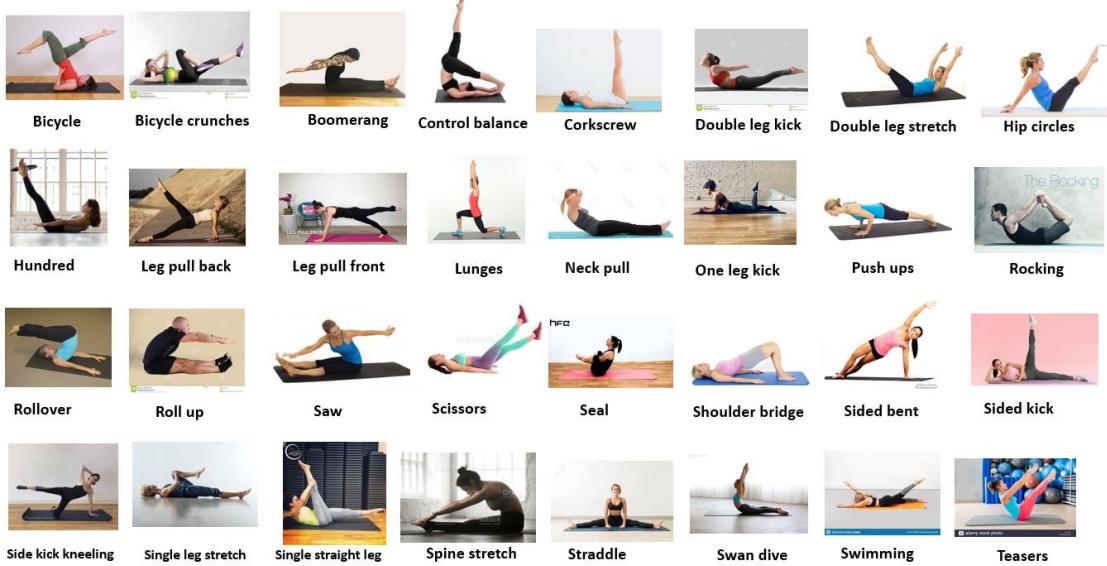


Figure A4. **Pilates Dataset:** Sample images of each of the 20 poses in the Pilates dataset.



Figure A5. **Lord of the dance:** Figure illustrates the correct, incorrect and CARE-generated poses of the Lord of the dance Yoga pose.



Figure A8. **Camel:** Figure illustrates the correct, incorrect and CARE-generated Camel pose.



Figure A6. **Warrior3:** Figure illustrates the correct, incorrect and CARE-generated poses of the Warrior 3 Yoga pose.



Figure A9. **Boat :** Figure illustrates the correct, incorrect and CARE-generated Boat pose.



Figure A7. **Bow:** Figure illustrates the correct, incorrect and CARE-generated Bow pose.



Figure A10. **Side Plank:** Figure illustrates the correct, incorrect and CARE-generated Side Plank pose.

Pose	ls	lh	lk	le	rs	rh	rk	re
HM: GT	114	67	178	177	78	178	178	173
Incorrect Pose	160	94	174	169	165	166	175	171
CARE CFE	160	94	174	169	168	166	175	171
LL: GT	172	128	138	171	166	75	72	172
Incorrect Pose	178	148	177	173	178	120	119	170
CARE CFE	178	104	177	173	178	120	119	170
LD	178	142	178	168	102	84	113	164
Incorrect Pose	114	67	178	177	78	178	178	173
CARE CFE	114	67	163	177	78	178	178	100
W3	160	94	174	169	165	166	175	171
Incorrect Pose	114	67	178	177	78	178	178	173
CARE CFE	114	67	178	106	22	178	178	173
Bow	76	96	109	157	86	92	102	188
Incorrect Pose	170	72	127	173	148	66	134	134
CARE CFE	170	72	127	173	148	66	134	130
CM	54	105	103	131	69	103	91	151
Incorrect Pose	44	135	96	171	175	146	95	162
CARE CFE	44	135	96	171	121	146	95	162
BT	47	70	162	111	74	74	162	126
Incorrect Pose	9	99	178	170	13	96	178	168
CARE CFE	9	99	178	170	61	47	178	168
SP	132	179	177	175	73	172	178	175
Incorrect Pose	22	177	178	172	73	168	174	160
CARE CFE	105	177	178	172	173	168	174	160

Table A1. **Correct, Incorrect and CFE generated pose:** HM: Half-Moon, LL: Low-Lunge, LD: Lord of the dance, W3: Warrior 3, CM: Camel, BT:Boat, SP:Side Plank

Dataset	Proximity	Threshold				
		1	2	3	4	5
Yoga-20	0.5	0.136	0.294	0.488	0.632	0.792
	5	0.134	0.286	0.474	0.638	0.786
	15	0.126	0.28	0.474	0.628	0.778
ASL	Threshold					
		0.5	1	1.5	2	2.5
	0.5	0.464	0.886	0.992	0.996	0.998
	5	0.462	0.89	0.996	0.996	1
	15	0.466	0.876	0.996	0.998	0.998
Pilates	Threshold					
		1	2	3	4	5
	0.5	0.188	0.532	0.82	0.9	0.928
	5	0.198	0.51	0.786	0.864	0.92
	15	0.17	0.482	0.77	0.898	0.932

Table A2. **Ablation Study on Proximity Weight:** Table shows the percentage of corrected poses for various thresholds of Mean Absolute Difference (MAD) error. We experiment with 3 different proximity weight values for each of the three datasets, while keeping the diversity weight constant.