NTU-X: An Enhanced Large-scale Dataset for Improving Pose-based Recognition of Subtle Human Actions

Neel Trivedi
neel.trivedi@research.iiit.ac.in
CVIT, IIIT Hyderabad
Hyderabad 500032, INDIA

Anirudh Thatipelli
at794@snu.edu.in
CVIT, IIIT Hyderabad
Hyderabad 500032, INDIA

Ravi Kiran Sarvadevabhatla
ravi.kiran@iiit.ac.in
CVIT, IIIT Hyderabad
Hyderabad 500032, INDIA

ABSTRACT

The lack of fine-grained joints (facial joints, hand fingers) is a fundamental performance bottleneck for state of the art skeleton action recognition models. Despite this bottleneck, community's efforts seem to be invested only in coming up with novel architectures. To specifically address this bottleneck, we introduce two new pose based human action datasets - NTU60-X and NTU120-X. Our datasets extend the largest existing action recognition dataset, NTU-RGBD. In addition to the 25 body joints for each skeleton as in NTU-RGBD, NTU60-X and NTU120-X dataset includes finger and facial joints, enabling a richer skeleton representation. We appropriately modify the state of the art approaches to enable training using the introduced datasets. Our results demonstrate the effectiveness of these NTU-X datasets in overcoming the aforementioned bottleneck and improve state of the art performance, overall and on previously worst performing action categories. Code and pretrained models can be found at https://github.com/skelemoa/ntu-x.

CCS CONCEPTS

• **Computing methodologies** → **Activity recognition and understanding**; **Artificial intelligence**; **Computer vision**; **Computer vision tasks**;

KEYWORDS

human action recognition, skeleton, dataset, human activity recognition, pose estimation

1 INTRODUCTION

Understanding human actions from visual data is crucial for applications related to surveillance, interactive user interfaces and multimedia systems. This task is usually accomplished with RGB

First two authors contributed equally.

videos as input [12]. However, advances in technologies have enabled use of other modalities (e.g. depth [17]) and systems such as Microsoft Kinect which can provide skeleton-like human pose representations [13]. In particular, the introduction of large-scale skeleton-based human action datasets NTU RGB+D [8, 14] has shifted the focus towards skeleton-based human action recognition approaches. In contrast to full-frame RGB-based representations, 3D skeleton joints encode human body dynamics in a computationally efficient manner, preserve privacy and can offer greater robustness to view and illumination.

The recent adoption of graph neural networks which process the skeleton action sequence as a spatio-temporal graph has enabled a steady rise in average accuracy for skeleton action recognition [3, 9, 15, 16, 20]. However, an analysis of sorted per-class accuracies reveals that the actions with lowest accuracy involve the usage of fingers (see Table 3,4). The underlying reason is that hand joints in Kinect-based skeletons provided in the original dataset are represented by just two finger joints (Figure 1-d). As a result, actions involving subtle finger movements (e.g. 'eating', 'writing', 'make ok sign', 'make victory sign') often fail to be recognized correctly. Sometimes, even the non-hand, main body joints are localized poorly by the Kinect-based capture system, as Figure 2 shows. These shortcomings at raw data level cannot be addressed at the architecture level, i.e. by proposing novel architectures.
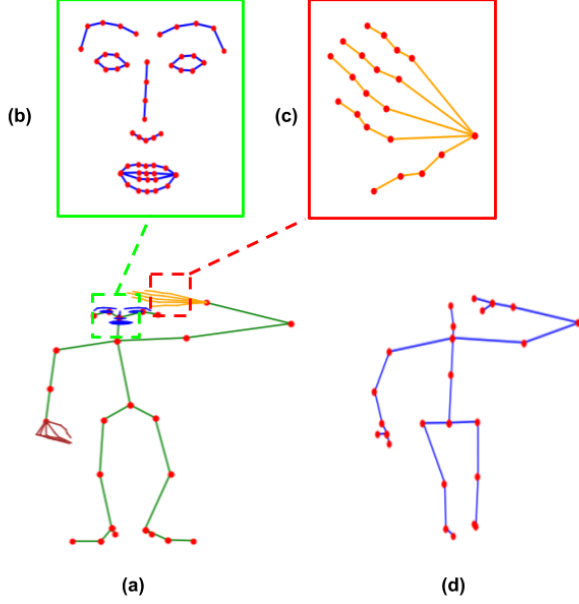
To address the mentioned data-level issues, we introduce NTU60-X and NTU120-X, curated and extended versions of the existing NTU dataset. Obtained from RGB videos present along with NTU skeleton data, the pose representations in the new dataset include 42 finger joints (21 for each hand), 51 facial keypoint joints and 25 body joints similar to those present in Kinect-based NTU-60 and NTU-120, for a total of 118 joints per skeleton (see Figure 1). We also modify state of the art approaches to enable experimental evaluation and benchmark the modified variants on NTU60-X and NTU120-X. As a result, we set the new state of the art benchmark on NTU-60 and NTU-120. Our results also demonstrate the benefit of the newly introduced datasets for overcoming the performance bottleneck mentioned earlier and enabling recognition of subtle human actions involving hand-based joints. Resources (source code, pre-trained models, analysis and videos) related to NTU-X will be made available.

2 RELATED WORK

Prior to creation of NTU RGB-D dataset, a number of datasets enabled progress for skeleton-based human action recognition. MSR-Action3d [7] was one of the first action recognition datasets which provided depth and skeleton joint modalities, albeit from a single viewpoint. However, it only covered a limited set of gaming

Figure 1: (a) The 118 **joint skeleton introduced in the new NTU-X datasets. The** 25 **body joints are indicated by red dots.(b)** 51 **facial joints (c)** 21 **finger joints (d)** 25 **body joints present in original NTU datasets .**

actions (e.g. forward punching, side boxing). The Northwestern-UCLA dataset [18] scaled up the diversity to include videos from multiple views and with actions performed by 10 different actors. The NTU RGB-D 60 dataset [14] comprises of 60 action categories, performed by 40 subjects. Its extension NTURGB-D 120 [8] is one of the largest and most diverse skeleton action dataset comprising of 120 actions performed by 106 subjects from 155 viewpoints.

Varying-view RGB-D Action Dataset (VAD) [6] comprises view-varying Kinect captured sequences covering the entire 360° view angles, containing 40 actions that are performed by 118 distinct performers. Unfortunately, the full dataset is not publicly available (as of current). Notably, the datasets mentioned above do not provide fine-grained joints for hands and faces which limits their utility for certain actions as mentioned previously.

An alternative approach for skeleton estimation infers the joints from RGB video frames without requiring specialized capture equipment. In the Kinetics-skeleton dataset [20], the 2D skeleton joint coordinates predicted from RGB frames are combined with the joint estimation confidence to obtain a pseudo 3D skeleton representation on videos from Kinetics-400 action dataset [2]. However, the resulting skeleton dataset contains many invalid sequences [5].

We summarize the salient aspects of these datasets and our proposed NTU60-X and NTU120-X in Table 1.

3 NTU-X

The NTU RGB+D dataset [14] provides RGB videos along with 3D Kinect skeleton data. We first extract the RGB frames from the videos at the frame rate of 30 FPS. We estimate 3D poses from RGB

frames using SMPL-X [11]. SMPL-X uses strong 2D pose priors estimated using Openpose [1] on each RGB frame. However, SMPL-X based pose estimation is rather slow and is reliant on optimization heuristics. It also fails on blurred images and in the presence of light occlusion. To compensate for these issues, we use ExPose [4]. ExPose uses a part-wise attention-based model that feeds high resolution patches of the corresponding body parts to their dedicated refinement module. Unlike SMPL-X, ExPose estimates the full 3D pose (body, finger and face joints) from the RGB image without relying on 2D pose prior and is much faster compared to SMPL-X.

Since it is difficult to automatically select between SMPL-X and ExPose pose representations, we employ a semi-automatic approach to curate the final dataset. We use Openpose [1] toolbox to estimate the 2D pose and associated confidence for the full-body joints. Openpose provides total 70 joints for face out of which we use 51 major joints as shown in Figure 1(b) to make the final skeleton of 118 joints (25 body + 21 × 2 fingers + 51 face) for each frame of the clips. Keeping the intra-view and intra-subject variance of the NTU dataset in mind, we sample random videos covering each view per class of NTU and estimate the SMPL-X and ExPose outputs. We examine the quality of the skeleton backprojected to RGB frame and use the accuracy of alignment to select between ExPose and SMPL-X. Empirically, we observe that ExPose and SMPL-X perform equally well for single-person actions but SMPL-X, though slow, provides better pose estimates for multi-person action class sequences. Kindly refer to the supplementary to check which pose extraction method (ExPose or SMPLx) has been used for each of the classes in the NTU-X dataset.

To ensure good dataset quality, we remove corrupted videos from the original dataset, using a procedure similar to one adopted for the original dataset [14]. We also omit videos in which people are completely absent. Additionally, for some classes such as 'hugging', OpenPose provides poor estimates when one of the two people involved are in close proximity. We discard instances of such videos as well.

4 EXPERIMENTS

To evaluate the impact of NTU60-X and NTU120-X on overall performance, we benchmarked models with state-of-the-art performance on NTU60 and NTU120. We selected DSTA-Net[15], 4s-ShiftGCN [3], MS-G3D [9] and PA-ResGCN [16] as the models to benchmark the newly introduced datasets. For the models DSTA-Net[15], MS-G3D [9] and 4s-ShiftGCN [3], we updated the graph structure of the skeletons to incorporate the newly introduced joints.

PA-ResGCN [16], being a semantic part-based model, required more significant modification. Along with changes in input skeleton graph structure as done for the other two models, we defined new parts to incorporate the newly introduced joints and thus enable richer feature extraction. Since this model learns attentive weights for each of the input skeleton joints by dividing the skeleton into different parts, the definition of parts were also changed based on the NTU-X skeleton. In case of NTU-RGBD skeleton, PA-ResGCN defines total 5 parts: torso, left arm, right arm, left leg and right leg. In the new NTU-X skeleton, 3 additional parts were defined for 67 joints (body + fingers) skeleton: left fingers, right fingers and head,
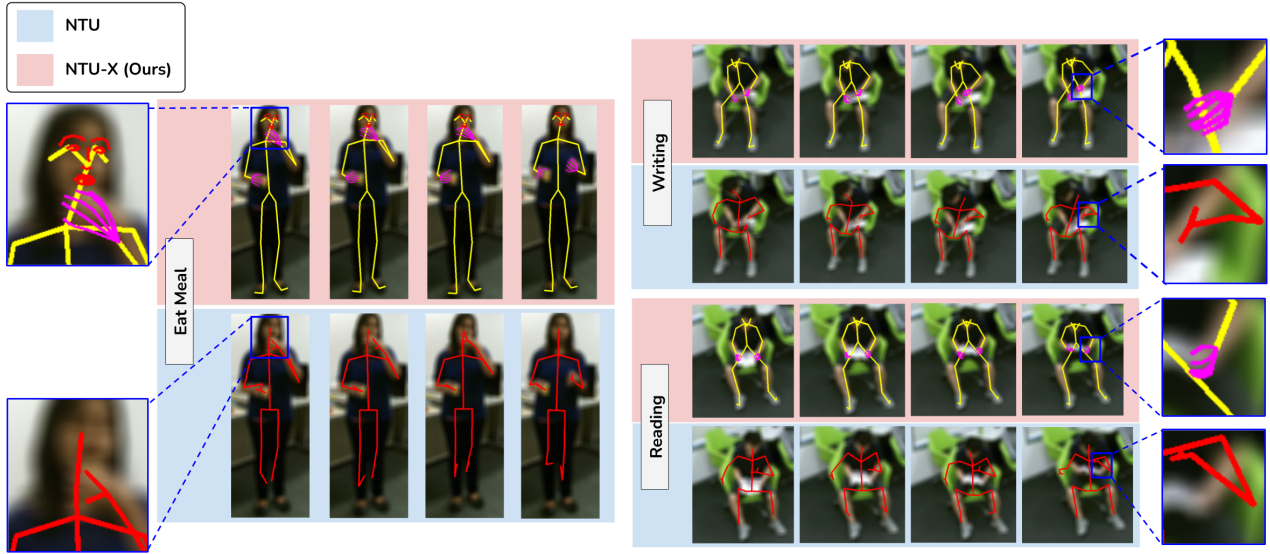
Figure 2: Sample skeletons from original NTU Kinect dataset (blue background) and proposed NTU-X dataset (pink background). Note that blurred RGB frame is included only for reference and is not part of skeleton data. The three classes mentioned - 'eat meal', 'writing' and 'reading' are few of the most confused classes for NTU dataset (see Table 3). As the zoomed insets illustrate, the quality of joints captured by NTU-X dataset is better compared to the original NTU dataset.

Dataset	Body	Face	Fingers	Sequences	Classes	Joints
MSR-Action3D[7]	✓			567	20	20
Northwestern-UCLA[18]	✓			1,475	10	21
VAD[6]	✓			25,600	40	25
NTU RGB+D[14]	✓			56,880	60	25
NTU RGB+D 120[8]	✓			114,035	120	25
NTU60-X (Ours)	✓	✓	✓	56,148	60	118
NTU120-X (Ours)	✓	✓	✓	113,821	120	118

Table 1: Comparison between NTU-X and some of the other publicly available skeleton-action recognition datasets. We are one of the first datasets to include body, face and hands joints in 3D for multi-person and occlusion case as well.

model	NTU60	NTU60-X (Ours)	NTU120	NTU120-X (Ours)
DSTA-Net[15]	91.50	**93.56**	86.60	**87.80**
4s-ShiftGCN[3]	90.70	**91.78**	85.90	**86.18**
MS-G3D[9]	91.50	**91.76**	86.9	**87.10**
PA-ResGCN[16]	90.9	**91.64**	**87.4**	86.42

Table 2: Results for top performing models of NTU60 and NTU120 dataset on NTU60-X dataset and NTU120-X (with finger joints) - see Section 4.1. The gray shaded columns show results on our newly introduced dataset. The blue highlighted cell corresponds to best overall performance for 60 and 120 class setups.

Model	Class name	NTU-60	NTU60-X
DSTA-Net [15]	Writing	67.04 %	79.41 %
	Reading	68.75 %	94.49 %
	Play with phone/tablet	71.06 %	86.91 %
	Type on a keyboard	71.64 %	93.45 %
	Sneeze or cough	73.55 %	80.07 %
4s-ShiftGCN [3]	Writing	65.19 %	76.23 %
	Reading	68.75 %	91.91 %
	Eat meal	72.89 %	80.22 %
	Type on keyboard	73.82 %	91.24 %
	Sneeze or cough	73.91 %	75.72 %
MS-G3D [9]	Writing	57.41 %	72.96 %
	Eat meal	71.43 %	79.85 %
	Reading	72.43 %	92.28 %
	Sneeze or cough	77.17 %	80.80 %
	Play with phone/tablet	78.75 %	79.41 %
PA-ResGCN [16]	Writing	63.97 %	78.89 %
	Reading	67.65 %	94.12 %
	Sneeze or cough	73.91 %	76.45 %
	Type on keyboard	74.91 %	91.61 %
	Eat meal	74.91 %	80.95%

Table 3: The NTU60 column shows accuracies of bottom 5 action classes for models trained on original NTU60 dataset. The NTU60-X column shows accuracies of the same classes but with models trained on our NTU60-X dataset (finger joints: Section 3). Thanks to availability of additional finger joint information in NTU-60X, we see visible performance improvement across all the models.

Model	Class name	NTU-120	NTU120-X
DSTA-Net [15]	Staple book	37.65 %	36.60 %
	Make ok sign	51.13 %	72.70 %
	Make victory sign	53.85 %	60.49 %
	Counting money	59.65 %	84.91 %
	Blow nose	64.94 %	70.73 %
4s-ShiftGCN [3]	Staple book	35.9 %	34.19 %
	Make victory sign	53.32 %	62.59 %
	Make ok sign	55.83 %	64.35 %
	Counting money	61.93 %	82.11 %
	Blow nose	63.07 %	67.60 %
MS-G3D [9]	Staple book	32.57 %	34.50 %
	Make victory sign	54.02 %	68.18 %
	Hit with object	60.03 %	69.98 %
	Blow nose	60.45 %	68.64 %
	Counting money	60.70 %	90.53 %
PA-ResGCN [16]	Staple book	40.63 %	36.08 %
	Make victory sign	59.79 %	60.49 %
	Hit with object	61.90 %	63.53 %
	Cutting paper	63.30 %	55.32 %
	Counting money	64.65 %	78.25 %

Table 4: The NTU120 column shows accuracies of bottom 5 action classes for models trained on original NTU120 dataset. The NTU120-X column shows accuracies of the same classes but with models trained on our NTU120-X dataset (finger joints: Section 3). Thanks to availability of additional finger joint information in NTU-120X, we see visible performance improvement across all the models.

resulting in a total of 8 parts. For 118 joint (body + fingers + face) skeleton along with these 3 additional parts, one more part of face was added resulting in a total of 9 parts.

4.1 Results

The results of training the four selected models on the new NTU60-X and NTU120-X datasets, with finger joints included for Cross Subject protocol, are shown in Table 2. Clearly, our modified DSTA-Net, MS-G3D, 4s-Shift-GCN and PA-ResGCN outperform their counterparts' performance on the original NTU60 dataset by a significant margin. For NTU120-X, all three models except PA-ResGCN outperform their counterparts' performance on NTU120 dataset. PA-ResGCN fails to surpass the orginal accuracy for 120 class dataset by a small margin. We hypothesize that this could be due to PA-ResGCN's architecture being too specific for the original Kinect skeleton setup and unable to handle the addition of extra added finger joints in the large-category (120 class) setting. We can also see that DSTA-Net not only beats its numbers on the original dataset, but also achieves state of the art performance among all the models with a margin of more than 2% for NTU60 dataset.(See highlighted cells in Table 2).

These results also support the fact that existing approaches, if provided better and richer joint data, have the capacity to perform better. A detailed analysis of each model's performance and category level improvements is discussed next.

4.2 Discussion

Table 3 and Table 4 list the five worst performing classes for all the four models on the original NTU60 and NTU120 datasets respectively along with their per class accuracy. The shaded columns in these tables provide the accuracy of these classes when the models are trained using the newly introduced NTU60-X and NTU120-X dataset. From these results, it is evident that most of the bottom performing classes for the original NTU datasets involve actions with fine finger movements (e.g. "writing", "type on keyboard", "eat meal", "make ok sign", "make victory sign"). When the models are provided with input data that includes finger joints, the per class accuracy for such categories is improved significantly. Figure 2 also shows that without inclusion of finger level joints, recognition of such action categories is ambiguous and difficult.

	Bottom-5 NTU60-X	Bottom-5 NTU120-X
DSTA-Net [15]	Writing (79.41 %) Eat meal (80.0 %) Sneeze or cough (80.07 %) Touch head (headache) (80.73 %) Take off a shoe (84.67 %)	Staple book (36.6 %) Make victory sign (60.49 %) Cutting paper (61.26 %) Fold paper (68.17 %) Play magic cube (69.47 %)
4s-ShiftGCN [3]	Sneeze or cough (75.72 %) Writing (76.3 %) Eat meal (80.22 %) Touch head (headache) (80.36 %) Playing with phone/tablet (80.51 %)	Staple book (34.15 %) Cutting paper (52.01 %) Playing with phone/tablet (60.73 %) Fold paper (61.22 %) Make victory sign (62.59 %)
MS-G3D [9]	Writing (72.59 %) Eat meal (79.12 %) Wear a shoe (80.07 %) Punching/slapping other person (80.66 %) Sneeze or cough (81.52 %)	Staple book (34.5 %) Fold paper (61.91 %) Cutting paper (63.18 %) Playing with phone/tablet (64.73 %) Make ok sign (65.91 %)
PA-ResGCN [16]	Sneeze or cough (76.45 %) Writing (78.89 %) Touch head (headache) (78.91 %) Punching/slapping other person (80.66 %) Eat meal (80.95 %)	Staple book (38.53 %) Cutting paper (55.32 %) Make victory sign (61.19 %) Playing with phone/tablet (61.45 %) Fold paper (62.78 %)

Table 5: This table shows the bottom performing classes for all the models evaluated in this paper on the newly introduced NTU60-X and NTU120-X datasets. This table clearly indicates that the overall accuracy of bottom performing classes for the newly introduced NTU60-X and NTU120-X are higher than the overall accuracy of bottom performing classes for the orginal datasets, as shown in Table 3 and Table 4

Table 5 shows the worst performing classes for the NTU-X dataset for all the models. Comparing with accuracy of worst performing classes of the original NTU dataset given in Table 3 and Table 4, we see that even the accuracy of worst performing classes of NTU-X dataset is, on average, higher compared to the original NTU dataset.

To further illustrate the performance boost we gain by including the finger level joints into the input skelton, we show the change in per class accuracy when going from orginal NTU dataset to newly introduced NTU-X dataset in Figure 3 and Figure 4 for the top performing model DSTA-Net[15](based on Table 2).

The table provided in the inset of Figure 3 shows classes which are benefited the most when going from NTU60 to NTU60-X dataset for the state-of-the-art performer (DSTA-Net). It is easy to see that these classes predominantly involve finger level actions such as "reading", "typing on keyboard", "playing with phone" and "writing". One can also observe that the gain for these classes is as high as **10-23 %**. A similar trend can be seen in Figure 4 which shows classes which benefit the most when going from NTU120 to NTU120-X dataset. Once again, the classes with highest gain involve finger level actions (e.g. "make of sign","hush") and the gain for these

classes is in the range **17-25%**. Both of these tables clearly indicate training recognition approaches on our proposed NTU-X dataset significantly boosts the performance of classes involving finger movements.

From Figure 3 and Figure 4, we also note that training on NTU-X dataset (finger joints) is not beneficial for all the classes, with a performance drop seen in some cases. Most of these classes involve another person (e.g. "hugging other person", "take photo of other person", "playing rock-paper scissors" etc.). As per our understanding, capturing accurate skeletons for multiple people in a RGB frame is difficult which leads to poor pose extraction and ambiguity in classifying the sequences involving multiple people.

However, it is clear that the overall magnitude of gain is higher than the magnitude of drop in per class accuracy. Hence, the average accuracy is higher for NTU-X dataset than the original NTU dataset.

4.3 Ablation Study

To examine the importance of body joints, finger joints and face joints individually, we also perform experiments with only body joints (25 joints), body + finger joints (67 joints) and body + fingers + face joints (118 joints) as well. The results of ablation study are

% change in per class accuracy for DSTA-Net on NTU60-X dataset

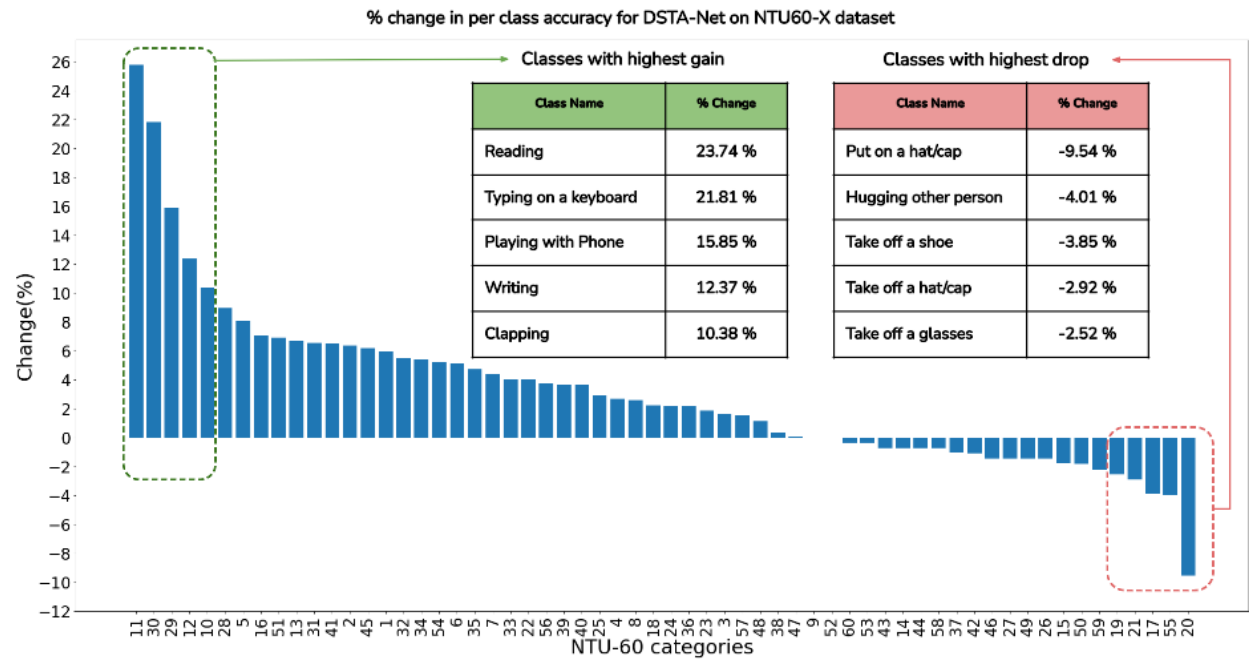| Classes with highest gain		Classes with highest drop	
Class Name	**% Change**	**Class Name**	**% Change**
Reading	23.74 %	Put on a hat/cap	-9.54 %
Typing on a keyboard	21.81 %	Hugging other person	-4.01 %
Playing with Phone	15.85 %	Take off a shoe	-3.85 %
Writing	12.37 %	Take off a hat/cap	-2.92 %
Clapping	10.38 %	Take off a glasses	-2.52 %

Figure 3: The % gain in per class accuracy for best performing model (DSTA-Net) after training on newly introduced NTU60-X dataset. The x-axis shows category id. The inset tables show actions with largest and least gain.

% change in per class accuracy for DSTA-Net on NTU120-X dataset

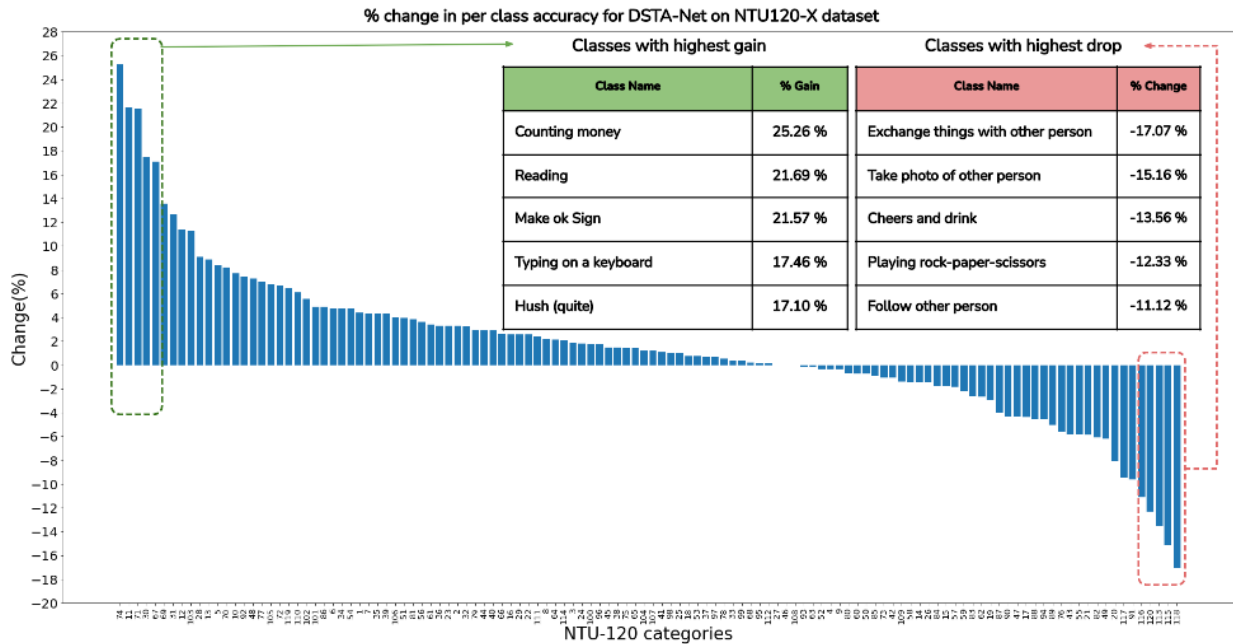| Classes with highest gain		Classes with highest drop	
Class Name	**% Gain**	**Class Name**	**% Change**
Counting money	25.26 %	Exchange things with other person	-17.07 %
Reading	21.69 %	Take photo of other person	-15.16 %
Make ok Sign	21.57 %	Cheers and drink	-13.56 %
Typing on a keyboard	17.46 %	Playing rock-paper-scissors	-12.33 %
Hush (quite)	17.10 %	Follow other person	-11.12 %

Figure 4: The % gain in per class accuracy for best performing model (DSTA-Net) after training on newly introduced NTU120-X dataset. The x-axis shows category id. The inset tables show actions with largest and least gain.

shown in Table 6. The performance degrades when face joints are included with the body and finger joints. One reason for this could

model	NTU60-X			NTU120-X	
	body	body + fingers	body + fingers + face	body	body + fingers
DSTA-Net[15]*	89.69	**90.91**	88.97	84.82	**87.80**
4s-ShiftGCN[3]	89.56	**91.78**	89.64	84.78	**86.18**
MS-G3D[9]	91.26	**91.76**	91.12	84.50	**87.10**
PA-ResGCN[16]	89.98	**91.64**	89.79	82.85	**86.42**

Table 6: Results on different variants of NTU60-X and NTU120-X dataset to understand the contribution of the additional joints. (*: Ablations on DSTA-Net are done using only the Joint stream of the network which contributes most to its performance.)

be that the actions in NTU dataset do not involve significant facial motion. Hence, the additional joints of the face make the skeleton graph larger than necessary and difficult for model optimization. Another possible reason could be that the existing models do not have a suitable architecture to handle the dense subgraph arising from the presence of facial keypoints. The poor results of models trained with only body joints (25 joints) are also in line with our hypothesis that the inclusion of finger joints in the input skeleton is crucial for better performance. In other words, the performance gain is not merely due to the shift from Kinect-based to RGB-based skeleton generation process.

5 CONCLUSION

In this paper, we have shown that the lack of hand-level joints is a fundamental performance bottleneck in the skeleton data of the largest action recognition dataset, NTU-RGBD. To address this bottleneck, we contribute a carefully curated skeleton dataset which provides finger-level hand joints and facial keypoint joints.

We appropriately modify the state of the art approaches to enable training using the introduced dataset. Our results demonstrate the effectiveness of the proposed dataset in enabling the modified approaches to overcome the aforementioned bottleneck and improve their performance, overall and on previously worst performing action categories. We also perform experiments to evaluate the relative importance of the introduced joints. We believe our contribution of new, expanded joint dataset will meet the twin objectives of improving performance and encouraging novel approaches in future. Going forward, we expect the research community to devise novel and efficient approaches for tackling dense skeleton representations present in our dataset.

Our 118 joints dataset, consisting of full body, fingers and even face joints can improve the recognition of actions based on expressions. This can help in capturing subtle changes in expression that would help in recognizing fine-grained actions (e.g. 'moving head up' and 'shaking head'). The significance of our work also arises from the emerging trend of fusing skeletal representations with other modalities (depth, RGB) for better performance in out of context, in-the-wild action recognition scenarios [5, 10, 19]. The pretrained deep networks we introduce serve as a good starting point for such fusion based approaches.

6 ACKNOWLEDGEMENTS

REFERENCES

[1] Z. Cao, G. Hidalgo Martinez, T. Simon, S. Wei, and Y. A. Sheikh. 2019. OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields. *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2019).

[2] João Carreira and Andrew Zisserman. 2017. Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset. *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2017), 4724–4733.

[3] Ke Cheng, Yifan Zhang, Xiangyu He, Weihan Chen, Jian Cheng, and Hanqing Lu. 2020. Skeleton-Based Action Recognition with Shift Graph Convolutional Network. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[4] Vasileios Choutas, Georgios Pavlakos, Timo Bolkart, Dimitrios Tzionas, and Michael J. Black. 2020. Monocular Expressive Body Regression through Body-Driven Attention. In *European Conference on Computer Vision (ECCV)*. https://expose.is.tue.mpg.de

[5] Pranay Gupta, Anirudh Thatipelli, Aditya Aggarwal, Shubh Maheshwari, Neel Trivedi, Sourav Das, and Ravi Kiran Sarvadevabhatla. 2021. Quo Vadis, Skeleton Action Recognition? *International Journal of Computer Vision* (05 May 2021). https://doi.org/10.1007/s11263-021-01470-y

[6] Yanli Ji, Feixiang Xu, Yang Yang, Fumin Shen, Heng Tao Shen, and Wei-Shi Zheng. 2019. A large-scale varying-view RGB-D action dataset for arbitrary-view human action recognition. *arXiv preprint arXiv:1904.10681* (2019).

[7] Wanqing Li, Zhengyou Zhang, and Zicheng Liu. 2010. Action recognition based on a bag of 3d points. In *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition-Workshops*. IEEE, 9–14.

[8] Jun Liu, Amir Shahroudy, Mauricio Perez, Gang Wang, Ling-Yu Duan, and Alex C. Kot. 2019. NTU RGB+D 120: A Large-Scale Benchmark for 3D Human Activity Understanding. *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2019). https://doi.org/10.1109/TPAMI.2019.2916873

[9] Ziyu Liu, Hongwen Zhang, Zhenghao Chen, Zhiyong Wang, and Wanli Ouyang. 2020. Disentangling and Unifying Graph Convolutions for Skeleton-Based Action Recognition. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[10] Gyeongsik Moon, Heeseung Kwon, Kyoung Mu Lee, and Minsu Cho. 2021. IntegralAction: Pose-driven Feature Integration for Robust Human Action Recognition in Videos. In *The IEEE Conference on Computer Vision and Pattern Recognition Workshop (CVPRW)*.

[11] Georgios Pavlakos, Vasileios Choutas, Nima Ghorbani, Timo Bolkart, Ahmed A. A. Osman, Dimitrios Tzionas, and Michael J. Black. 2019. Expressive Body Capture: 3D Hands, Face, and Body from a Single Image. In *Proceedings IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*.

[12] Ronald Poppe. 2010. Poppe, R.: A Survey on Vision-based Human Action Recognition. Image and Vision Computing 28(6), 976-990. *Image Vision Comput.* 28 (06 2010), 976–990. https://doi.org/10.1016/j.imavis.2009.11.014

[13] Bin Ren, Mengyuan Liu, Runwei Ding, and Hong Liu. 2020. A Survey on 3D Skeleton-Based Action Recognition Using Learning Method. (2020). arXiv:2002.05907 [cs.CV]

[14] Amir Shahroudy, Jun Liu, Tian-Tsong Ng, and Gang Wang. 2016. NTU RGB+D: A Large Scale Dataset for 3D Human Activity Analysis. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[15] Lei Shi, Yifan Zhang, Jian Cheng, and Hanqing Lu. 2020. Decoupled Spatial-Temporal Attention Network for Skeleton-Based Action-Gesture Recognition. In *ACCV*.

[16] Yi-Fan Song, Zhang Zhang, Caifeng Shan, and Liang Wang. 2020. Stronger, Faster and More Explainable: A Graph Convolutional Baseline for Skeleton-Based Action Recognition. In *Proceedings of the 28th ACM International Conference on Multimedia (ACMMM)*. Association for Computing Machinery, New York, NY, USA, 1625–1633. https://doi.org/10.1145/3394171.3413802

[17] Jiang Wang, Zicheng Liu, Ying Wu, and Junsong Yuan. 2012. Mining Actionlet Ensemble for Action Recognition with Depth Cameras. IEEE International Conference on Computer Vision and Pattern Recognition (CVPR).

[18] Jiang wang, Xiaohan Nie, Yin Xia, Ying Wu, and Song-Chun Zhu. 2014. Crossview Action Modeling, Learning and Recognition. arXiv:1405.2941 [cs.CV]

[19] Philippe Weinzaepfel and Gregory Rogez. [n.d.]. Mimetics: Towards Understanding Human Actions Out of Context. *arXiv* ([n. d.]).

[20] Sijie Yan, Yuanjun Xiong, and Dahua Lin. 2018. Spatial Temporal Graph Convolutional Networks for Skeleton-Based Action Recognition. In *AAAI*.