

Quo Vadis, Skeleton Action Recognition?

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Abstract—In this paper, we study current and upcoming frontiers across the landscape of skeleton-based human action recognition. To begin with, we benchmark state-of-the-art models on the NTU-120 dataset and provide multi-layered assessment of the results. To examine skeleton action recognition ‘in the wild’, we introduce Skeletics-152, a curated and 3-D pose-annotated subset of RGB videos sourced from Kinetics-700, a large-scale action dataset. The results from benchmarking the top performers of NTU-120 on Skeletics-152 reveal the challenges and domain gap induced by actions ‘in the wild’. We extend our study to include out-of-context actions by introducing Skeleton-Mimetics, a dataset derived from the recently introduced Mimetics dataset. Finally, as a new frontier for action recognition, we introduce Metaphorics, a dataset with caption-style annotated YouTube videos of the popular social game Dumb Charades and interpretative dance performances. Overall, our work characterizes the strengths and limitations of existing approaches and datasets. It also provides an assessment of top-performing approaches across a spectrum of activity settings and via the introduced datasets, proposes new frontiers for human action recognition.

Index Terms—human action recognition, human activity recognition, skeleton, 3-D human pose, deep learning

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1 INTRODUCTION

UNDERSTANDING human actions, especially from their 2-D and 3-D joint-based skeleton representations, has received a lot of focus recently. Joint-based representations have a small memory footprint which improves feasibility of on-board processing in compute-restricted environments (e.g. smartphones, cameras on IoT devices). The privacy-friendly nature of the skeleton representation is also an advantageous factor.

On the flip side, obtaining accurate 3-D skeleton data usually requires specialized capture mechanisms and constraints on the capture environment. Even after the capture hurdle is crossed, the sparsity of skeleton representation relative to denser counterparts (RGB, depth) induces ambiguity and imposes additional challenges. In addition, the lack of large-scale, diverse datasets remained a challenge until the advent of datasets such as NTU-60 [1] and PKU-MMD [2]. These datasets have prompted a number of diverse approaches for skeleton-based action recognition [3], [4], [5], [6], [7], [8], [9]. The introduction of the even larger NTU-120 dataset [10] is poised to continue this trend.

Typically, the introduction of a newer, larger dataset (NTU-120) is marked by a flurry of novel architectures which aim to solve challenging domain tasks. In this paper, we argue that this is also a good opportunity to evaluate approaches originally trained for earlier dataset versions and more generally, re-evaluate the status quo. This argument has already been made successfully for RGB action recognition [11]. To this end, we benchmark current, past state-of-the-art approaches on the NTU-120 dataset and analyze the results (Sec. 3).

The datasets and capture methods for aforementioned works are confined to controlled, indoor settings. What about human activities occurring outdoors, ‘in the wild’? Also, in recent times, a number of works on robust estima-

tion of human 3-D pose from RGB data have emerged [12], [13], [14]. These prompt yet another question: How well can human actions be recognized in terms of 3-D skeletal pose estimated from RGB videos? To answer these questions, we first create Skeletics-152, a carefully curated and 3-D pose-annotated subset of videos sourced from Kinetics-700 [15], a large-scale RGB action dataset. Subsequently, we evaluate the performance of top ranked NTU-120 approaches (Sec. 4.1).

Actions in NTU-120 and Kinetics datasets retain either full or partial context supplied by object interactions and background. In contrast, out-of-context actions represent an unconventional and challenging frontier for skeleton action recognition. To benchmark performance for such actions, we evaluate the recognition models on the skeletal version of Mimetics [16], a subset of Kinetics-400 containing exaggerated, out-of-context human actions (Sec. 4.2). Additionally, we introduce Metaphorics, a new video dataset with detailed action phrase annotations for YouTube videos of the popular social game Dumb Charades and expert dance performances of popular songs (Sec. 6). The performance on skeleton version of Metaphorics provides an opportunity to study the capabilities and limitations of existing approaches which are typically optimized for non-interactive, category-based, closed-world recognition paradigms.

Overall, our work characterizes the strengths and limitations of existing approaches and datasets. It also provides an assessment of top-performing approaches across a spectrum of activity settings and via the introduced datasets, proposes new frontiers for human action recognition.

Our primary contributions can be summarized as follows:

- We benchmark current, past state-of-the-art skeleton action recognition approaches on a large-scale dataset (NTU-120) and provide insightful analysis of performance trends (Sec. 3).
- We introduce Skeletics-152, a curated 3-D pose anno-

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Fig. 1: A pictorial illustration of the landscape for skeleton-based action recognition. Datasets such as NTU-120 characterize actions in controlled lab-like settings. We use state-of-the-art RGB 3-D pose estimation to obtain skeletons and benchmark recognition models 'in the wild' by introducing SKELETICS-152 dataset. To explore out-of-context action recognition in the wild, we introduce SKELETON-MIMETICS and benchmark models trained on SKELETICS-152. As a novel frontier for action recognition, we introduce METAPHORICS which contains indirectly conveyed metaphor-style actions. Note that all datasets are skeleton-based – RGB background has been included to convey the original context.

tated subset of Kinetics-700 for benchmarking skeleton action recognition 'in the wild' (Sec. 4.1).

- We introduce Skeleton-Mimetics to recognize skeleton-based out-of-context and exaggerated actions (Sec. 4.2).
- We introduce Metaphorics, a new video dataset with phrase annotations for YouTube videos of Dumb Charades and interpretative dance to explore the new frontier of metaphor-style actions (Sec. 6).
- We provide a qualitative assessment of previously established recognition models on 3-D skeletal sequences from the Metaphorics dataset (Sec. 6).

The code, pre-trained models and datasets will be released. To enable richer understanding of performance characteristics across datasets and approaches, we also plan to open-source our interactive web-based visualization dashboard for the benefit of the community.

For better understanding, please refer to the video accompanying the paper at https://www.youtube.com/watch?v=YKjQcV_2gLU which depicts various skeleton action sequences from the datasets and associated model predictions.

2 RELATED WORK

Skeletons from explicit 3-D capture: An earlier era of works serve to document handcrafted features for skeleton action recognition [17], [18], [19], [20]. The recent class of approaches based on deep networks can be broadly categorized into three groups based on input skeleton data representation.

The first group explicitly consider the sequential nature of actions wherein the temporal dependencies are modelled using an RNN or an LSTM [21], [22], [23]. To further discriminate activities based on the joint dependencies, Song et al. [24] introduce attention mechanisms at multiple levels in the network. Kundu et al. [25] learn the action sequence as a trajectory in the pose manifold for the downstream activity classification task. Caetano et al. [26] use CNN-based feature representation over a temporal window containing skeleton dynamics.

The second group of works model the input skeleton as a single spatio-temporal unit. In some instances, this unit is a tensor of the form frames \times joints \times coordinates which is subsequently processed by a CNN [27], [28], [29], [30], [31]. More recently, a series of approaches use graph convolutions to model the (spatio-temporal) unit. Prominent examples include the ST-GCN framework introduced by Yan et al. [32] and variants [4], [8]. In contrast to the fixed graph in ST-GCN, newer approaches involve adaptation to learn the graph topology [3], [5], [7], [33], [34].

In addition to the groups mentioned above, hybrid approaches also exist. Si et al. [33] employ an attention-based graph convolutional LSTM to capture the spatio-temporal co-occurrence relationships. Zhang et al. [6] propose a CNN-RNN late-fusion model with learnable view transformation. For a survey of 3-D skeleton action recognition, refer to Presti et al. [35] and Wang et al. [36]. In addition to NTU-120 [10], numerous other 3-D skeleton datasets exist [1], [2], [18], [37], [38]. However, we consider NTU-120 in our work, given its dominance over existing datasets in terms of size, viewpoint and category diversity.

Skeletons from RGB video based pose: In another class of approaches, human skeletal pose estimated from in-the-wild RGB video frames is used for action recognition. A number of approaches based on 2-D skeleton pose from RGB video exist [39], [40], [41], [42], [43]. A recent variation involves a pseudo 3-D pose representation wherein 2-D OpenPose coordinates [44] in Kinetics-400 [45] videos are augmented with joint-level confidence scores as the third coordinate [3], [5], [7], [9], [32], resulting in the Skeleton-Kinetics dataset [32]. Weinzaepfel et al. [16] use 3-D pose obtained using LCR-Net++ [14] on Kinetics-400 and create a skeleton-based version of the dataset for pretraining models tasked with mimed action recognition. In our case, we build a curated subset of the much larger Kinetics-700 [15] dataset and utilize skeleton sequences obtained using VIBE [12], a state-of-the-art 3-D human pose estimation model, for benchmarking.

3 SKELETON ACTION RECOGNITION IN THE LAB

NTU-120 [10] is the largest 3-D skeleton action recognition dataset, comprising 114,480 25-joint 3-D skeleton annotated

Method	Cross Setup	Cross Subject
DGNN [3]	78.13	75.16
GCN-NAS [5]	85.29	81.99
2s-SDGCN [48]	86.18	84.42
VA-CNN (ResNeXt-101) [6] ¹	86.90	84.88
4s-ShiftGCN [47]	87.65	85.76
MS-G3D [46]	87.32	85.92
top-5 models average pooled	88.80	87.22

TABLE 1: Benchmarking comparison for NTU-120 test set (mean accuracy). Gray-shaded lines correspond to models which originally reported results on NTU-60 but retrained by us on NTU-120 for comparison.

videos of 120 human actions, performed by 106 subjects in a controlled indoor setting and captured from 32 different camera viewpoints.

3.1 Evaluation Protocol

Two standard evaluation protocols are typically used for evaluation of multi-subject multi-viewpoint skeleton action recognition approaches. In the Cross Subject protocol, the train and test set are split based on performer id. Under the protocol proposed by Liu et al. [10] for NTU-120, 53 subject ids out of 106 are allocated for training and the remaining for test. We use data from 11 (20%) randomly selected ids of original training set for validation.

The other protocol is Cross Setup. By default, action sequences from the 16 even-numbered camera setup ids are used for training and 16 odd setup ids are used for testing. As with cross subject protocol, we retain the original NTU-120 test set and use 4 (25%) ids randomly chosen from even setup ids for validation.

3.2 Performance with full sequences

For benchmarking comparison, we selected approaches which report performance on NTU-120 and top 5 approaches with the best performance on NTU-60 [1], the precursor to NTU-120. The results on the test set of NTU-120 can be viewed in Table 1. The results show that MS-G3D [46] and 4s-Shift-GCN [47] are the best performers for Cross Setup and Cross Subject respectively.

The gray-shaded portion of Table 1 shows the performance of top performing NTU-60 models evaluated on the NTU-120 test set. Note that these models were not originally designed for NTU-120 and were retrained by us from scratch, for benchmarking purposes. From the results, we notice that our version of VA-NN [6], retrained with a more powerful backbone (ResNeXt-101) performs competitively with state-of-the-art NTU-120 approaches (MS-G3D and 4s-Shift-GCN). VA-CNN has a relatively simpler architecture and is fast to train, adding to its appeal. More significantly, the results underscore the importance of benchmarking existing approaches on newly introduced datasets while investing effort into creation of novel architectures.

Figure 2 shows the mean accuracy and associated standard deviation for the top-5 models. The significant magnitude of deviation indicates that additional progress is

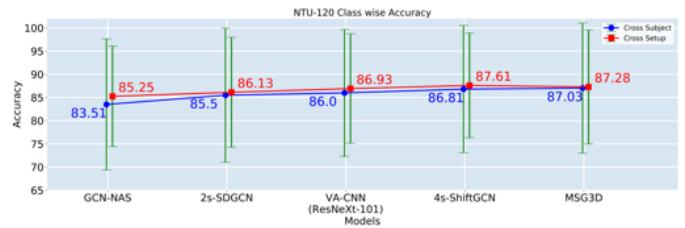


Fig. 2: Class accuracy plots for NTU-120 with standard deviation

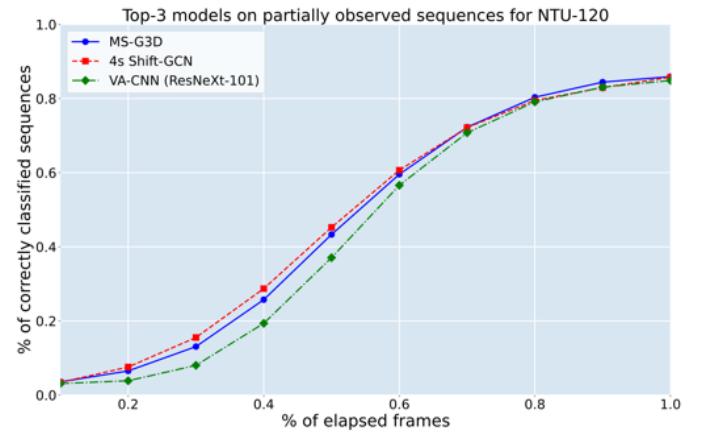


Fig. 3: Comparison of top-3 models on the partially observed sequences for NTU-120 (Cross Subject)

needed before mean accuracy can be considered a reliable measure of overall performance.

To obtain a better understanding of performance, we list the 10 best recognized and worst recognized action classes in Table 2 (cross subject) and Table 3 (cross setup). The results show that the best and worst performers largely stay same across all the models. The best performing classes (e.g. 'Arm swings', 'Jump up', 'Walking towards') have distinct actions and involving large joint-level movements. On the other hand, action classes containing subtle actions with fine-grained differences are hardest to recognize and exhibit large intra-class confusion (Figure 4). For instance, 'Make ok sign' and 'Make victory sign' get confused with each other significantly because the actions differ only in terms of hand joint movement which is not captured in adequate detail by the Kinect sensor. In addition, skeletons for classes such as 'Reading' and 'writing' have very low inter-class variability, resulting in poor performance.

The top 5 models exhibit similarities at the set level for top-10 and bottom-10 classes. However, motivated by the variance in actual rank order (Tables 2,3), we examine performance with an average pooled ensemble of top-5 models. In addition to being the new state-of-the-art, the noticeably improved ensemble performance (bottom row of Table 1) suggests that the top-5 models span action classes in a complementary manner.

1. Our version of VA-CNN [21] with ResNeXt-101 backbone.

	MS-G3D	4s-ShiftGCN	VA-CNN	2s-SDGCN	2s-AGCN
Top-10	Hugging	Jump up	Falling down	Stand up	Hugging
	Hopping	Staggering	Walking towards	Jump up	Drink after cheers
	Put on jacket	Take off jacket	Jump up	Walking towards	Arm swings
	Walking Towards	Arm swings	Arm swings	Drink after cheers	Put on jacket
	Drink after cheers	Put on jacket	Pushing	Arm circles	Run on the spot
	Jump up	Walking towards	Staggering	Put on Jacket	Arm circles
	Staggering	Arm circles	Arm circles	Arm swings	Jump up
	Arm circles	Hugging	Squat down	Staggering	Staggering
	Arm swings	Run on the spot	Drink after cheers	Take off jacket	Walking towards
	Capitulate	Drink after cheers	Follow	Hugging	Follow
Bottom-10	Staple book	Staple book	Make ok sign	Staple book	Staple book
	Make victory sign	Make victory sign	Make victory sign	Make victory sign	Make ok sign
	Hit with object	Make ok sign	Staple book	Writing	Make victory sign
	Blow nose	Counting money	Counting money	Counting money	Counting money
	Counting money	Blow nose	Play with phone or tablet	Make ok sign	Writing
	Writing	Reading	Reading	Cutting nails	Cutting paper
	Reading	Cutting paper	Writing	Blow nose	Hit with object
	Make ok sign	Hit with object	Hit with object	Play with phone or tablet	Blow nose
	Snap fingers	Cutting nails	Fold paper	Wield Knife	Cutting nails
	Cutting nails	Play with phone or tablet	Play magic cube	Hit with object	Yawn

TABLE 2: Top-10 and Bottom-10 classes for models trained on NTU-120 (Cross Subject)

	4s-ShiftGCN	MS-G3D	VA-CNN	2s-SDGCN	2s-AGCN
Top-10	Put on jacket	Stand up	Walking towards	Walking towards	Walking towards
	Walking towards	Nod head or bow	Falling down	Put on jacket	Put on jacket
	Staggering	Put on jacket	Jump up	Stand up	Stand up
	Jump up	Walking towards	Staggering	Nod head or bow	Hopping
	Stand up	Arm circles	Hopping	Walking apart	Arm circles
	Walking apart	Hopping	Stand up	Hopping	Staggering
	Take off jacket	Staggering	Arm swings	Arm circles	Nod head or bow
	Hopping	Arm swings	Walking apart	Jump up	Cheer up
	Nod head or bow	High five	Cross toe touch	Take off jacket	Drink after cheers
	Cross toe touch	Walking apart	Nod head or bow	Sit down	Walking apart
Bottom-10	Staple book	Writing	Make ok sign	Staple book	Cutting paper
	Writing	Staple book	Staple book	Writing	Play magic cube
	Make ok sign	Cutting paper	Writing	Cutting paper	Make ok sign
	Cutting paper	Make ok sign	Counting money	Yawn	Staple book
	Yawn	Counting money	Reading	Counting money	Make victory sign
	Make victory sign	Cutting nails	Yawn	Cutting nails	Counting money
	Wield knife	Yawn	Make victory sign	Make ok sign	Writing
	Counting money	Wield knife	Cutting paper	Make victory sign	Yawn
	Reading	Reading	Play with phone or tablet	Reading	Type on keyboard
	Cutting nails	Make victory sign	Hit with object	Play magic cube	Cutting on nails

TABLE 3: Top-10 and Bottom-10 classes for the models trained on NTU120 (Cross Setup)

3.3 Performance on partial sequences

Action recognition from partially observed sequences has been an active area of research [49], [50], [51], [52] and has many practical applications in the field of video surveillance and human-computer interaction. The ambiguity induced by partial sequences naturally makes this a challenging problem. To study action recognition in this setting, we benchmark the top-3 models of Table 1 on the partially observed skeleton sequences of NTU-120 using the Cross Subject protocol in Figure 3. The increase in accuracy is on expected lines, i.e. actions are generally better recognized when the extent to which they are seen increases. In particular, the multiple input streams in 4s-ShiftGCN and MS-G3D learn complementary features. Therefore, with increasing % of elapsed frames, these models outperform VA-CNN by a noticeable margin.

To understand recognition onset trends in a fine-grained

manner, we replicate the plot of Figure 3, but now for the top-1 model (MS-G3D) and for individual action categories. The top-5 and bottom-5 classes by *overall* accuracy can be viewed in Figure 5. The closer a curve to the top-left corner, the better its ability to be recognized early. From this viewpoint, it is interesting to note that some classes (top-3,4) ranked lower than the overall top-most have earlier onset of recognition. The temporal effect of intra-class confusion on bottom ranked classes can also be seen.

The top-5 and bottom-5 plots in Figure 5 are with respect to *overall*, 100% elapsed performance. As a better alternative for measuring early recognition performance, we propose the Area-under-curve (AUC) - the closer a category's AUC to 1, the earlier it can be recognized. The top-5 and bottom-5 categories by AUC can be viewed in Figure 6. Multiple interesting trends can be seen. Firstly, most of the top-5 and bottom-5 classes are different from overall accuracy

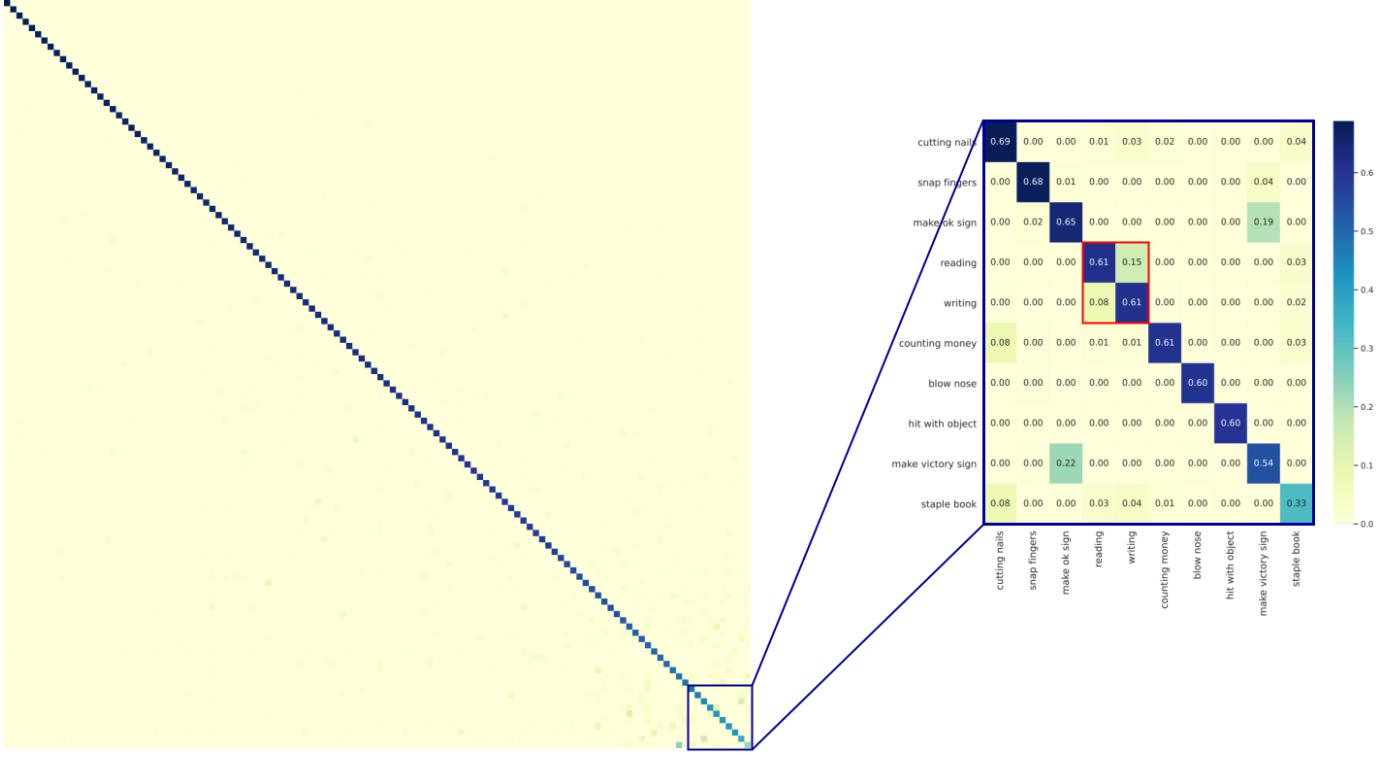


Fig. 4: The confusion matrix sorted by class-wise accuracy shows that the least accurately recognized classes are confused amongst each other (magnified inset).

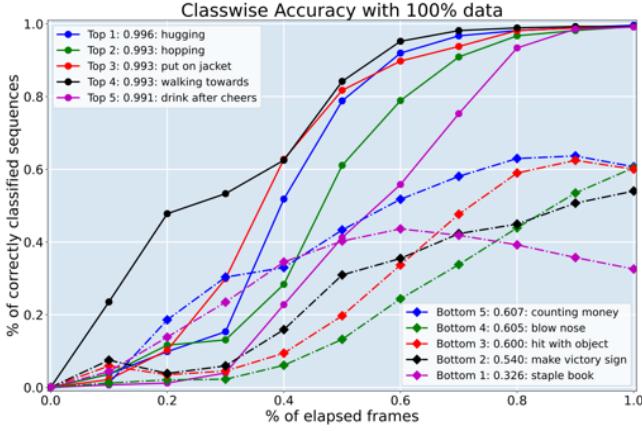


Fig. 5: Early recognition curves for top-5, bottom-5 classes of MS-G3D model on NTU-120 Cross Subject with class-wise accuracy as the measure.

plot counterparts. The AUC-wise top performing classes (e.g. 'Walking towards', 'Walking apart' and 'Take off jacket') contain minimal intra-class variation and are more consistently identified with increasing number of frames. The accuracy of 'Point finger' class decreases in the first half due to barely discernible joint movement in the initial frames. Among the AUC-wise bottom classes ('Snap fingers', 'Make victory sign', 'Make OK sign'), the finger-joint motion is predominant. Since hand joints are not captured adequately in NTU-120, a fundamental bottleneck arises in recognizing these classes regardless of elapsed time.

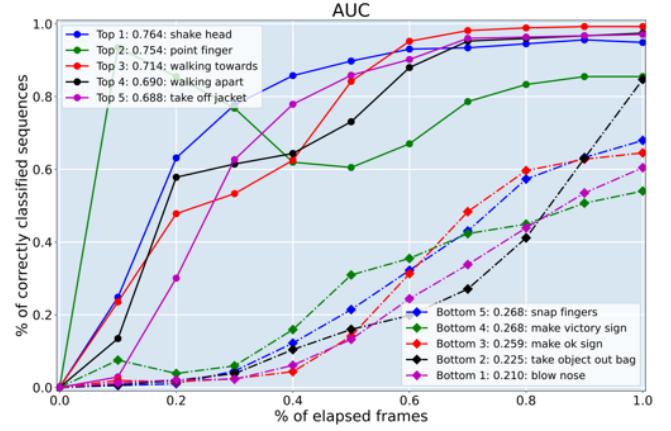


Fig. 6: Early recognition curves for top-5, bottom-5 classes of MS-G3D model on NTU -120 Cross Subject with AUC as the measure.

4 SKELETON ACTION RECOGNITION IN THE WILD

As mentioned in the Introduction (Sec. 1), large-scale datasets such as NTU-120 represent lab-style, controlled, indoor settings. In contrast, a much larger variety of human actions characterize in-the-wild RGB videos of human activities. To obtain 3-D skeleton representations from such videos, pose estimation techniques are applied on action sequences from large-scale activity datasets. In this section, we explore two diverse settings with progressively increasing level of complexity in terms of human actions.



Fig. 7: Examples of classes from Kinetics-700 omitted for skeleton action recognition. In 'Playing American football', multiple people are detected. For 'Playing ice hockey' and 'Somersaulting', pose estimation is not accurate. In 'Springboard diving', the person performing the diving action is not tracked.

4.1 Skeletics-152

For our experiments, we use Kinetics-700 [15], a large-scale video dataset consisting of over 650,000 YouTube video clips spanning over 700 action categories ranging from daily routine activities, sports and other fine-grained actions. However, unlike previous work (Skeleton-Kinetics-400 [32]), we carefully omit categories from action settings which are incompatible for pose-based skeleton action recognition.

- A number of classes (e.g. 'Petting cat', 'Scrubbing face') were removed because most of the videos contain occluded poses which make the 3D pose estimation unviable.
- Some classes (e.g. 'Cooking eggs', 'Wrapping presents', 'Clay pottery making') were removed as they were captured from egocentric views.
- Some classes (e.g. 'Peeling apples', 'Peeling potatoes', 'Baking cookies') are highly object-centric and hence, irrelevant for skeleton based action recognition.
- Classes involving no substantial movement (e.g. 'Staring', 'Attending a conference') cannot be recognised solely based on human pose.
- Classes where the labels differ solely due to scene background were removed (e.g. 'Walking through snow' is same as 'Walking').

On videos from the 274 categories that remain, we use VIBE [12] to obtain corresponding 3-D skeleton sequences. Classes such as 'Playing american football', 'Playing ice hockey', 'Doing aerobics', containing large groups of people performing different activities were removed based on VIBE detections. In addition, classes such as 'Somersaulting', 'Springboard diving' were removed since the VIBE model typically reported missing joints. Figure 7 shows some examples of omitted action classes. For the case of multiple (> 2) skeleton detections in videos, we select the top two skeletons appearing in maximum number of frames. For any intermediate frames with missing skeleton detections, we perform bounding box and joint interpolation. In the end, we obtain Skeletics-152, our curated 3-D skeleton dataset which contains 125,621 sequences spread over 152 classes.

As with NTU-120, we use dataset splits originally provided with Kinetics-700. To enable comparison, we use the original validation set of Kinetics-700 as our test set. We randomly split the original Kinetics-700 training set into training and validation sets in a 85:15 ratio. To address class imbalance, we employ class-frequency based mini-batch resampling and class-based loss weighting.

Model	Accuracy	F-1 score
MS-G3D (trained from scratch)	56.39	50.80
4s-ShiftGCN (trained from scratch)	56.15	50.41
MS-G3D (pretrained on NTU-120 + finetuned)	55.75	49.57
4s-ShiftGCN (pretrained on NTU-120 + finetuned)	57.01	51.13

TABLE 4: Results on Skeletics-152 test set with mean accuracy as performance measure.

	MS-G3D	4s-ShiftGCN
Top-5	Mountain climber (exercise) Front raises Jumping Jacks Deadlifting Lunge	Mountain climber (exercise) Clean and jerk Front raises Lunge Jumping jacks
Bottom-5	High fiving Cumbia Falling off chair Hugging (not baby) Combing hair	Falling off chair Cumbia Swinging baseball bat Passing American football (not in game) Digging

TABLE 5: Top-5 and Bottom-5 classes of all models trained on Skeletics-152 dataset.

We evaluated the best two performers (MS-G3D and 4s-ShiftGCN) from NTU-120 in two training regimes. In one regime, we first extracted VIBE skeletons from RGB videos of NTU-120 and trained the models on these skeletons. The resulting models were ultimately fine-tuned on the Skeletics-152 data. In the second regime, we trained the models from scratch on Skeletics-152 data. We found that 4s-ShiftGCN provides the best performance (Table 4). Pre-training on NTU-120 provides a slight benefit compared to training from scratch. Comparing the performance rates in Tables 1 and 4, it is evident that skeleton-based action recognition in the wild is significantly more challenging given the inter/intra-category diversity and noise-inducing factors (e.g. occlusion, lighting, uncontrolled background context). In addition, we empirically observed that even the best 3-D pose estimators routinely generate poorly localized joint estimates, impacting performance.

As shown in the Table 5, the top-5 classes are all exercise based activities which tend to have very low intra class variability. On the other hand, sequences from the bottom-5 classes exhibit a lot of diversity and intra-class variability (see Figure 8).

4.2 Skeleton-Mimetics

Human actions in the wild tend to be contextual. Such context can be valuable and does influence traditional (RGB)

Pose estimator	Base Model	Training set	Test set	Mean Accuracy
LCR-Net++ [14]	SIP-Net [16]	Kinetics-400 (50 classes) Kinetics-400 (full)	Mimetics (50 classes) Skeleton-Mimetics (23 classes)	25.10 21.57
VIBE	MS-G3D	Skeletics-152 (full)	Skeleton-Mimetics (23 classes)	57.37
		Skeletics-152 (23 classes)		49.22
	4s-ShiftGCN	Skeletics-152 (full)		56.11
		Skeletics-152 (23 classes)		51.10

TABLE 6: Performance summary on Skeleton Mimetics dataset.

action recognition approaches. However, this sometimes causes context to excessively influence model predictions for RGB models [11]. Skeleton-based approaches are not affected by context. Context arises from two sources – objects involved in the action and background in which action takes place. Actions in NTU-120 occur in the absence of background context but objects associated with actions are present. How do action recognition approaches fare when objects are absent as well?

The Mimetics dataset [16] was introduced to study and develop recognition models for out-of-context actions where objects are absent. Derived as a subset of Kinetics-400 (an earlier version of Kinetics-700), Mimetics contains 713 RGB videos spread over 50 out-of-context action classes performed by expert mimicry artists. The actions often include gesture-like, exaggerated movements. We followed the same data curation procedure as Skeletics-152 (Sec. 4.1) to extract 3-D pose from RGB videos. Our final dataset, Skeleton-Mimetics, contains 319 skeleton sequences across 23 classes (out of 50 present in Mimetics). An important observation in Skeleton-Mimetics is that the actions mimicked by actors without object interactions are often exaggerated. Also, actors in Mimetics sometimes describe the physically absent (virtual) object as part of the action performance (e.g. opening a bottle, climbing a rope). Such descriptions do not happen in physical object interaction settings (e.g. Kinetics). Therefore, Skeleton-Mimetics dataset poses unique challenges and is a novel frontier for skeleton action recognition.

Following the procedure for its parent dataset [16], we perform only evaluation on Skeleton-Mimetics. The results can be viewed in Table 6. For reference, the results on all 50 Mimetics classes and the 23 shortlisted by us are presented in the top-most segment. In general, we also observe that our models outperform existing approaches by a significant margin. This is likely due to our choice of powerful base models and the judicious curation of action classes (Skeletics-152) used to train the base model.

5 DISCUSSION

In this section, we analyze the salient trends for skeleton action recognition approaches and scenarios. The list of top-5 and bottom-5 classes for various scenarios (datasets) can be viewed in Table 7.

The first two columns correspond to the lab-based indoor datasets - NTU-60 and NTU-120. It is interesting to note that even the worst performing classes of NTU-60 have accuracy in the range 50-70 % while the counterparts in NTU-120 exist in a much lower range (32-60 %). One reason

is that the introduction of NTU-120 resulted in an increase of action classes with subtle, finger-level movements which impacts performance as mentioned previously (Section 3.3).

We have already seen that average performance in the wild is relatively lower compared to lab-based settings (Tables 1, 4). The results from Table 7 for Skeletics-152 reflect this trend as well. Actions in the wild exhibit large intra-class variability which affects even the top-5 classes (cf. top-5 of NTU-120). Actions belonging to the bottom-5 classes in Skeletics and Skeleton-Mimetics are characterized either by high intra-class variability or by containing subtle, finger-dominant motions which cannot be captured by existing skeleton representations. Additionally, action sequences in NTU-120 are somewhat choreographed, having a defined starting pose and ending pose, but this is absent in Skeletics.

In terms of base architectures, MS-G3D provides the best performance across various datasets except for Skeletics-152, where 4s-ShiftGCN is the best performer. A pictorial illustration of performance trends in the top-2 models for selected action classes from Skeletics-152 and Skeleton-Mimetics can be viewed in Figure 8. Interestingly, even for the classes with lowest performance (bottom-3), the correct prediction for Skeletics is often in the list of top-5 model predictions. This is similar to the trend already observed for NTU-120 (Section 3).

To gain an overall perspective about the datasets, both existing ones and those introduced in our work, we summarize some prominent attributes in Table 8. Note that these cover both quantitative and qualitative aspects of the datasets.

Overall, our analysis motivates the need for approaches which can explicitly focus on boosting the performance for classes ranked lowest. Another complementary requirement arising from our analysis is for skeleton representations which provide finger-level joint information.

6 METAPHORICS DATASET

The action datasets encountered so far can be characterized as *verb*-based actions, since the action description is fundamentally incomplete without the verb. However, humans also tend to associate non-verb words to actions, iconic gestures being a well-known example [53]. In general, actions can be more abstract and used to convey metaphorical concepts. One such scenario is the popular social game of Dumb Charades. The game involves interactive and adaptive guessing of a target 'phrase'(usually a movie title) based on actions being performed by an 'actor'. Unlike other datasets, nouns and adjectives can have action de- pictions. Moreover, the vocabulary is open-ended, further

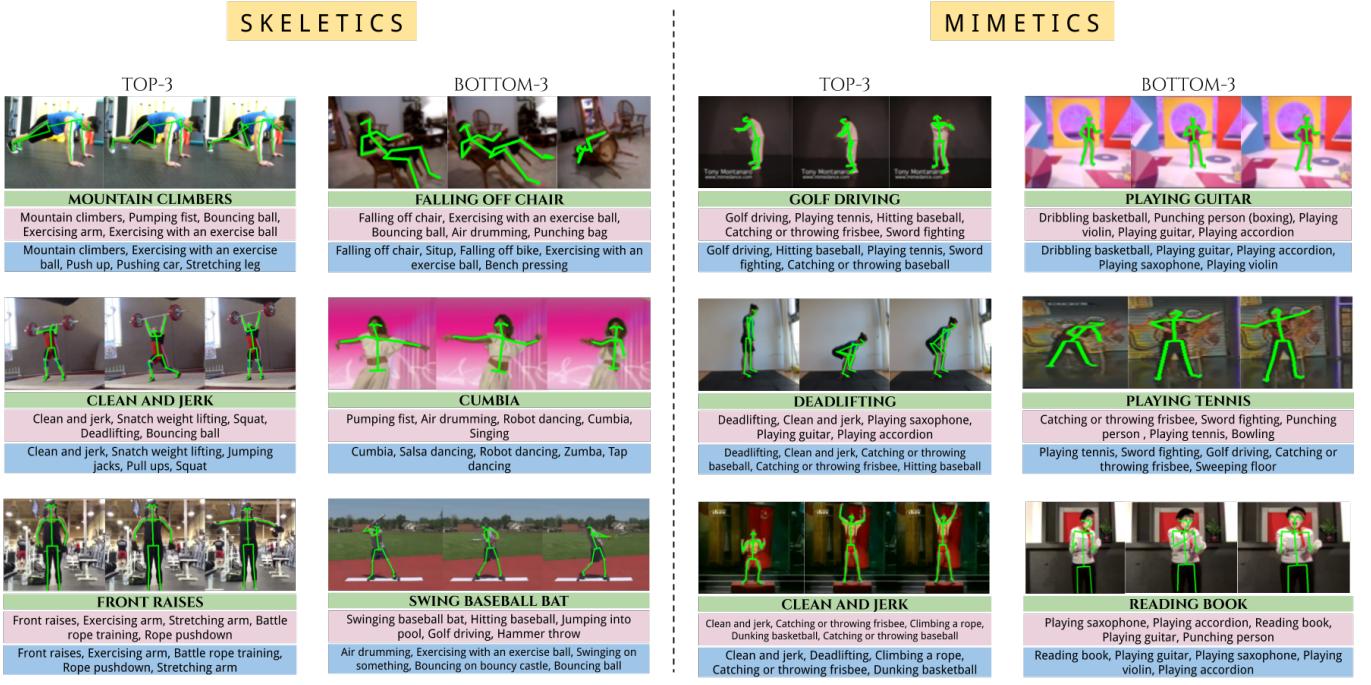


Fig. 8: Sample skeleton sequences from Skeletics-152 and Mimetics-Skeleton. The sequences are chosen from top-3 and bottom-3 classes in terms of performance achieved by best models on these datasets (see Tables 4, 6). The ground-truth phrase is color-coded green. The top-5 predictions by 4s-ShiftGCN are coded pink and those by MS-G3D are coded blue.

	NTU-60 [MS-G3D]	NTU-120 [MS-G3D]	SKELETICS-152 [4s-ShiftGCN, 25-joint]	SKELETON-MIMETICS [MS-G3D, 25-joint]
Top-5	Staggering (99.64%) Jump up (99.27%) Falling down (98.54%) Put on jacket (98.53%) Hopping (98.18%)	Hugging (99.64%) Hopping (99.27%) Put on jacket (99.27%) Walking towards (99.26%) Drink after cheers (99.13%)	Mountain climber (exercise) (92.59%) Clean and jerk (89.29%) Front raises (87.37%) Lunge (87.14%) Jumping jacks (87.10%)	Golf driving (93.33%) Deadlifting (90.00%) Clean and jerk (83.33%) Climbing a rope (78.57%) Playing saxophone (75.00%)
	Writing (57.41%) Eat meal (71.43%) Reading (72.43%) Sneeze or cough (77.17%) Play with phone or tablet (78.75%)	Staple book (32.57%) Make victory sign (54.02%) Hit with object (60.03%) Blow nose (60.45 %) Counting money (60.70%)	Falling off chair (11.5%) Cumbia (12.90%) Swinging baseball bat (14.29%) Passing American football (not in game) (16.28%) Digging (17.39%)	Playing tennis (15.79%) Playing guitar (16.67%) Reading a book (30.00%) Bowling (38.46%) Catching or throwing baseball (38.46%)

TABLE 7: List of Top-5 and Bottom-5 classes in terms of accuracy for NTU-60, NTU-120, Skeletics-152 and Skeleton-Mimetics datasets. The model associated with the best performance is in brackets alongside the dataset name.

	NTU-120	SKELETICS-152	SKELETON-MIMETICS	METAPHORICS
No. of Classes	120	152	23	N.A.
No. of sequences	114,480	125,657	319	845
Action Vocabulary	Fixed	Fixed	Fixed	Open-ended
Action setting	Lab/Scripted	Wild	Wild	Wild/Scripted
Action environment	Non-contextual	Contextual	Non-contextual	Non-contextual
Typical action duration	1-10 seconds	10 seconds	1-10 seconds	1-3 seconds
Level of action explicitness	High	High	Moderate	Low
Camera	Fixed	Fixed/Moving	Fixed	Fixed

TABLE 8: Attributes of datasets (existing, newly introduced) in the paper.

compounding the action understanding challenge. To study actions arising in this challenging scenario, we introduce Metaphorics, a new dataset. The dataset contains videos from two scenarios - dumb charades and interpretive dance.

Dumb Charades: We first source Dumb Charade game episodes from YouTube. In the game episodes, one person ('actor') acts out a target phrase word by word while the

other player tries to guess the target phrase solely from actions performed by the 'actor'. For annotation, we use the popular Anvil tool [54]. We annotate (i) target phrase (ii) beginning and ending timestamps for each action segment (iii) guess phrase associated with a segments (iv) episode outcome ('correctly guessed','incorrect'). We also annotate certain special actions such as number of words and the

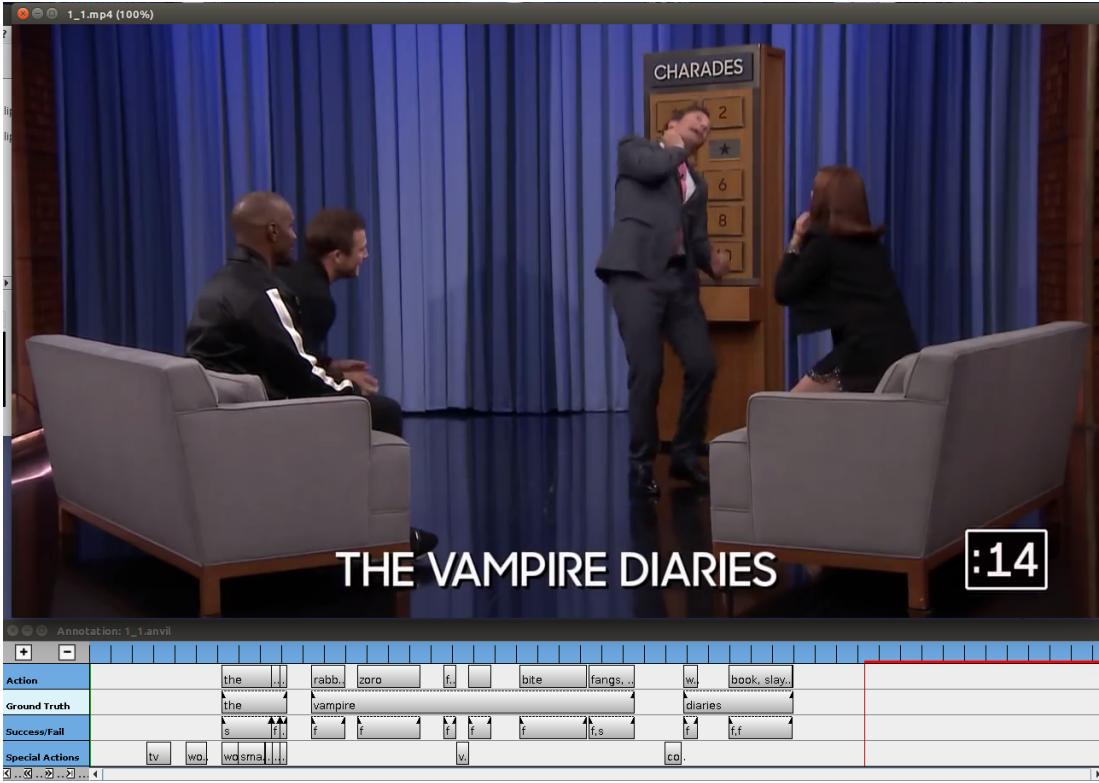


Fig. 9: An illustration of the annotation for a typical Charades episode using the Anvil interface. 'Action, Ground Truth, Success/Fail, Special Actions' are the annotation channels. In the 'Action' channel, 'rabb...(rabbit)' and 'zorro' are guesses that the guessing player makes for the first two actions performed by the actor performs upon being revealed the ground truth phrase 'the vampire diaries'. The segment labelled 'vampire' in the 'Ground Truth' channel is the entire duration for which the actor tried to act out the word 'vampire'. The 'Success/Fail' channel shows the success and failure for corresponding guesses present in the 'Action' channel. Here, 'rabbit' and 'zorro' are both incorrect and hence they are marked as 'F'. The 'Special Action' channel has tabs containing 'TV' and 'wo...(number of words)'. These are helping actions to indicate that the phrase is the name of a TV show and the number of words in the phrase respectively.

current word number for a multi-word target phrase. These special actions also include helping actions which the actor uses to convey some basic information to the guessers such as length of the word ('long', 'short'). Figure 9 provides an illustration of a typical annotation for a Charades video episode.

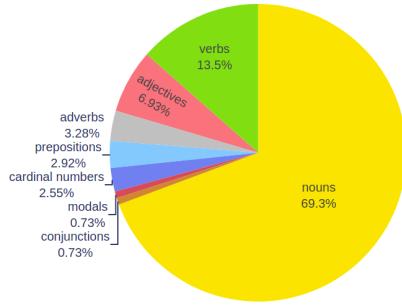


Fig. 10: Part of speech distribution across the ground-truth for Metaphorics dataset.

To characterize performance of action recognition approaches, we associate each correctly guessed word with its corresponding temporal video slice ('clip'). After removing clips where the actor is occluded, we obtain 716 such clips

across 28 game sessions.

Interpretative dance: We also source YouTube videos containing interpretative dances of popular songs. In these videos, the song is made audible only to the actor who then proceeds to enact real-time actions corresponding to song lyrics. In this case, the guesser needs to correctly guess the song title based on the performed lyric-based actions. Unlike Charades, the actor is required to act out the song lyrics in real time which increases the challenge since the actions are more fast paced than Charades. As part of the annotation process, we align the lyric subtitle file of original song and the video based on the starting point of the song (in the video). Since the actions are performed in real time, we obtain the action level annotations by aligning the audio file of the video with the original audio file of the song. The temporal extents of the dance are thus annotated into word-level action clips. We obtain a total of 129 clips across two full-length music videos.

In total, our Metaphorics dataset contains 845 video clips. Compared to existing datasets, videos tend to be 'bursty' due to the extremely small temporal extents of the actions. The dataset is very diverse in terms of the types of action sequences and the labels present (see Figure 10).

As with other RGB datasets, we obtain corresponding 3-D skeleton sequences using VIBE [12]. To obtain a qual-

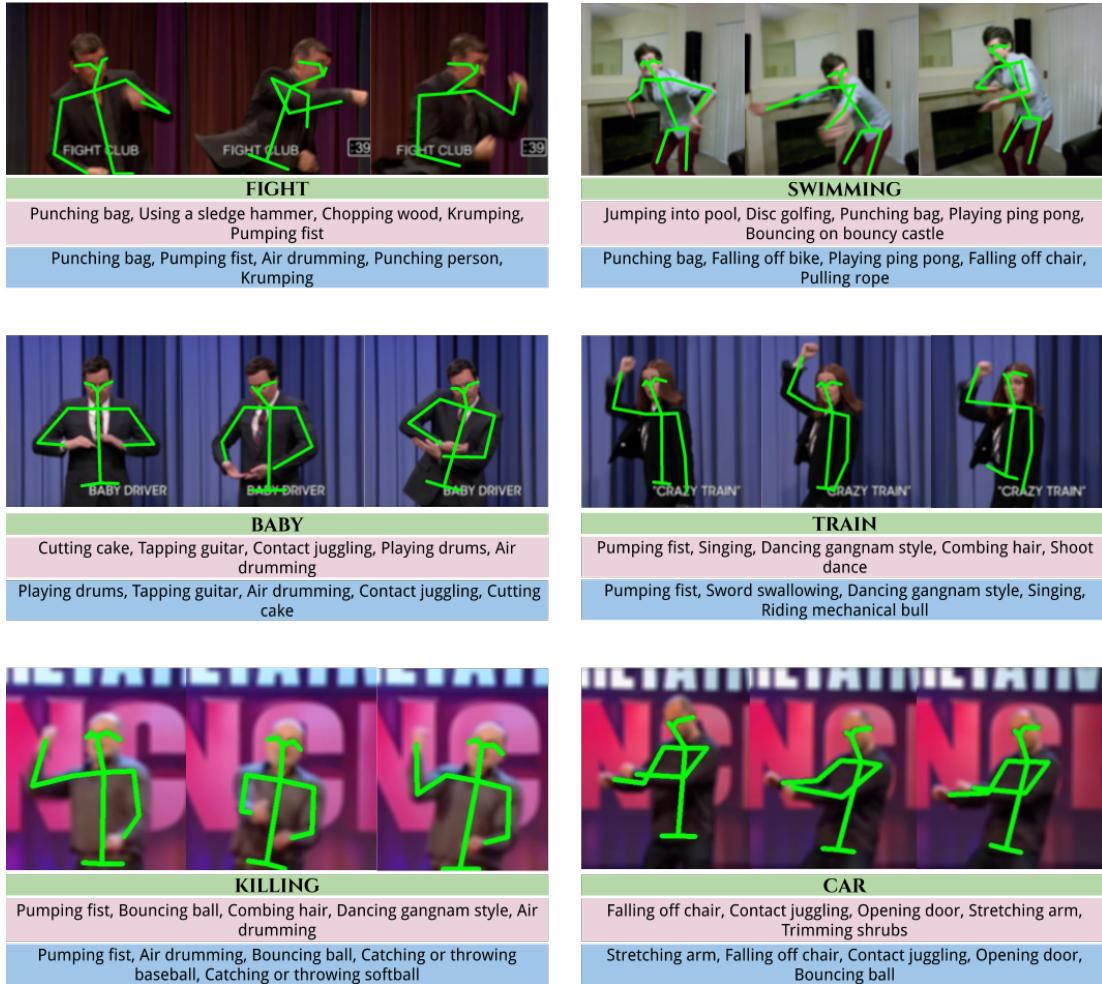


Fig. 11: Sample skeleton sequences from our Metaphorics dataset. The ground-truth phrase is color-coded green. The top-5 predictions by 4s-ShiftGCN are coded pink and those by MS-G3D are color-coded blue.

itative assessment of top-performing skeleton-based models, we report top-5 predictions by MS-G3D, 4s-ShiftGCN pre-trained on Skeletics-152 for sample videos from our dataset in Figure 11. As mentioned before, target phrases in Dumb Charades and interpretative dances are typically enacted indirectly using metaphors. Models trained on other datasets tend to map the skeleton sequence 'literally' to action labels. This explains some of the predictions seen in Figure 11. For example, the model predictions for actions shown in the first row seem related to the ground-truth tags ('fight', 'swimming'). The predictions for the other example sequences reinforce the literal nature of current action prediction models as mentioned previously.

7 CONCLUSION

In this paper, we have examined multiple existing and upcoming frontiers in the landscape of skeleton-based human action recognition. As an important facet of establishing new frontiers for skeleton action understanding in the wild, we curate and introduce three new datasets – Skeletics-152, Skeleton-Mimetics and Metaphorics. Our experiments and benchmarking reveal the capabilities and shortcomings of state-of-the-art recognition models. In addition, the results also highlight the bias induced by processing components

(e.g. RGB 3-D pose estimation) and the task paradigm (classification). We hope these findings and the newly introduced datasets will spur the design of better models for 'in the wild' actions – both contextual and non-contextual.

In our current work, we have not examined approaches which map skeleton actions to lexical phrase representations (cf. class labels) [55], [56]. We intend to study this promising frontier as well in the future.

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