

MV-Fashion: Towards Enabling Virtual Try-On and Size Estimation with Multi-View Paired Data

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Figure 1. We present **MV-Fashion**, a multi-view synchronized video dataset with 72.5 million frames. The dataset contains diverse clothing, multi-layered outfits annotated with draping styles, and paired catalogue domain data, ready for virtual try-on and fashion-centric tasks. The capture setup, shown in the middle, features 60 RGB cameras (blue) and 8 RGB-depth cameras (green) with 4K footage.

Abstract

Existing 4D human datasets fall short for fashion-specific research, lacking either realistic garment dynamics or task-specific annotations. Synthetic datasets suffer from a realism gap, whereas real-world captures lack the detailed annotations and paired data required for virtual try-on (VTON) and size estimation tasks. To bridge this gap, we introduce MV-Fashion, a large-scale, multi-view video dataset engineered for domain-specific fashion analysis. MV-Fashion features 3,273 sequences (72.5 million frames) from 80 diverse subjects wearing 3-10 outfits each. It is designed to capture complex, real-world garment dynamics, including multiple layers and varied styling (e.g. rolled sleeves, tucked shirt). A core contribution is a rich data representation that includes pixel-level semantic annotations, ground-truth material properties like elasticity, and 3D point clouds. Crucially for VTON applications, MV-Fashion provides paired data: multi-view synchronized captures of worn garments alongside their corresponding flat, catalogue images. We leverage this dataset to establish baselines for fashion-centric tasks, including virtual try-on,

clothing size estimation, and novel view synthesis. The dataset is available at:

<https://hunorlaczko.github.io/MV-Fashion>

1. Introduction

Understanding and modeling human clothing is fundamental for applications ranging from 3D games and digital avatars to animation and virtual try-on (VTON) systems. Accurately modeling 3D clothes enhances VTON, reduces designer workloads, and enables data-driven physics simulations. In e-commerce, accurately predicting fit and size is crucial to reduce retailer losses from returns caused by poor online fit assessment [21]. Developing realistic reconstruction and simulation algorithms also advances sustainability by reducing physical samples, overproduction, and the environmental impact of returns [21].

However, this research area presents significant challenges because garments exhibit substantial variability in terms of size, shape, topology, and fabric, which complicates the generation of representative 3D data. A core tech-

Dataset	Sizes	Styles	Layered	Subjects	Sequences	Outfits	Frames	RGB	Depth
4D-Dress [79]	×	×	✓	32	520	64	78K	53	×
GeneBody [10]	×	×	×	100	370	×	2.95M	48	×
ActorsHQ [30]	×	×	×	8	52	8	40K	160	×
SIZER [75]	✓	×	×	100	×	10	2K	130	×
X-humans [71]	×	×	×	20	×	×	35k	53	×
4DHumanOutfit [2]	×	×	×	20	1,540	140	459K	68	×
FeeMan [78]	×	×	×	40	8,000	×	11.3M	8	×
UltraStage [92]	×	×	×	100	×	×	192k	32	×
Neural Actor [46]	×	×	×	4	4	4	87K	86	×
ZJU-Mocap [64]	×	×	×	9	9	9	161K	21	×
MPI-INF-3DHP [55]	×	×	×	8	64	16	1.3M	14	×
NHR [81]	×	×	×	3	5	3	100K	80	×
CMU Panoptic [34]	×	×	×	97	65	97	15.3M	480	10
AIST++ [43]	×	×	×	30	1408	30	10.1M	9	×
HUMBI [87]	×	×	×	772	×	772	26M	107	×
Humman [7]	×	×	×	1,000	400K	1,000	60M	10	10
Human3.6M [29]	×	×	×	11	×	11	3.6M	4	1
THuman 4.0 [91]	×	×	×	3	×	3	10K	24	×
DyMVHumans [90]	×	×	×	32	2,668	45	8.2M	60	×
DNA-Rendering [11]	×	×	×	500	5K	1,500	67.5M	60	8
MVHumanNet++ [41]	×	×	×	4,500	60K	9,000	645.1M	48	×
Ours	✓	✓	✓	80	3,273	474	72.5M	68	8

(a) Comparison of multi-view human datasets.

Name	MV	Poses	Paired	Video	Outfits	Frames
DeepFashion [49]	×	✓ (4-5)	×	×	-	800K
DeepFashion2 [25]	×	✓	×	×	43.8K	491K
FashionPedia [31]	×	×	×	×	-	48,825
Fashion-Gen [68]	×	✓ (1-6)	×	×	-	293,008
Fashionista [83]	×	×	×	×	-	158,235
CloSe-D [1]	✓ (130)	✓ (7)	×	×	-	-
4DHumanOutfit [2]	✓ (68)	✓ (multiple)	×	✓	140	459K
DeepFashion3D [94]	✓ (50)	×	×	×	563	2,078
4D-DRESS [79]	✓ (53)	✓ (multiple)	×	✓	64	78K
VITON [26]	×	×	✓	×	16,253	32,506
VITON-HD [12]	×	×	✓	×	13,679	13,679
LookBook [86]	×	✓ (~8)	✓	×	9,732	84,748
FashionTryOn [89]	×	✓ (2)	✓	×	4,327	86,142
FashionOn [28]	×	✓ (2)	✓	×	10,895	32,685
MPV [19]	×	✓ (~3)	✓	×	13,524	35,687
DressCode [57]	×	✓ (2-5)	×	×	53,792	107,584
IGPair [70]	×	✓ (2-5)	✓	×	86,873	649,714
MVG [77]	×	✓ (5)	✓	×	1,009	5,045
VVT [20]	×	✓ (multiple)	✓	✓	791	190,101
TikTokDress [59]	×	✓ (multiple)	✓	✓	817	270K
ViViD [23]	×	✓ (multiple)	✓	✓	9,700	1.2M
Ours	✓ (68)	✓ (multiple)	✓	✓	474	72.5M

(b) Comparison of fashion-centric datasets.

Table 1. We compare the proposed **MV-Fashion dataset** with existing datasets, which we divide into two categories: (a) multi-view human, and (b) fashion-centric datasets. For the multi-view human comparison, we evaluate attributes such as *Size* (inclusion of clothing measurements), *Styles* (style variations of the same outfit), *Layered* (multiple clothing layers in the same outfit), *Subjects* (number of participants), and *Sequences* (number of videos), along with the number of *RGB* and *Depth* cameras in the capture setup. For the fashion-centric comparison, our criteria include: *MV* for Multi-View (use of multiple synchronized cameras), *Poses* (different poses in the same clothing; 'multiple' refers to video sequences with many poses), *Paired* (linking images of the worn outfit to garment photos) and *Video* (static images vs. video). In both cases, we also add *Outfits* (number of outfits), and *Frames* (number of RGB frames). In this table, wherever used, 'K' denotes thousands (10^3) and 'M' denotes millions (10^6). ✓ indicates available/yes, ✗ indicates not available/no/unspecified.

nical hurdle is modeling dynamic deformations, particularly those associated with loose clothing like dresses or coats, which often fail to be captured realistically by models relying solely on basic skeletal or parametric body priors.

While many fashion-centric datasets have been introduced, the current landscape remains fragmented. Research is largely split between two types of datasets, neither of which is sufficient on its own. Standard 2D VTON datasets [12, 57, 70] offer vital catalogue-to-worn image pairs but lack 3D geometric or multi-view data. Conversely, existing 3D and 4D fashion datasets [79, 94] capture geometry and motion but omit the paired catalogue data essential for VTON tasks. This creates a critical gap: no single dataset provides the synchronized multi-view data and the explicit catalogue-to-worn pairings required to jointly tackle garment dynamics, size estimation, and VTON.

Furthermore, existing datasets for dynamic human modeling, despite rapid progress, remain ill-suited for fashion-specific research. Synthetic datasets [4, 95] offer large-scale ground-truth but suffer from a realism gap, failing to capture complex garment dynamics. Meanwhile, real-world capture datasets like ActorsHQ [30], DNA-Rendering [11] and MVHumanNet++ [41] provide high-fidelity appearance and large-scale datasets but are designed for general human motion. They lack the specific focus, annotations, and data pairings useful for fashion-centric tasks. Finally, these high-

resolution, multi-view datasets introduce significant computational complexity and scalability challenges.

In this work, we introduce MV-Fashion, a new multi-view video dataset engineered specifically to bridge the gap between general multi-view human capture and domain-specific fashion analysis. We balance data quality and acquisition efficiency through a custom multi-view capture setup based on affordable, off-the-shelf hardware. Our dataset provides a unique combination of scale and fashion-centric detail, curated to address fundamental challenges in garment-centric applications. It explicitly captures complex clothing behaviors, such as multi-layering and diverse styling configurations (e.g., tucked shirts, rolled sleeves), thereby providing a robust benchmark for future research. To support applications in virtual try-on and clothing size estimation, we provide extensive ground-truth annotations. These include manually captured material properties (elasticity, fabric type), sizing charts, categorical labels, garment-level segmentations, body pose and shape estimations, and point clouds recovered from depth sensors. A key innovation for virtual try-on is the inclusion of paired flat/catalogue images of the garments for every multi-view video sequence. See Tab. 1 for a comprehensive comparison of MV-Fashion with other multi-view and fashion datasets. We leverage this comprehensive data to establish several baselines for virtual try-on, cloth size estimation, and novel

view synthesis.

In summary, our key contributions are:

- **A large-scale, multi-view video fashion dataset**, captured with a resource-friendly, multi-view setup using 68 cameras.
- **Unique, challenging capture scenarios** designed to test garment dynamics, with multi-layered outfits and diverse styling variations.
- **Rich, multi-modal data** essential for fashion applications, including pixel-level segmentations, ground-truth garment material/elasticity data for physics, categorical labels, detailed sizing charts, SMPL-X [63] pose and shape parameters, and 3D point clouds.
- **Catalogue-to-multi-view pairing** providing flat garment images for every multi-view video sequence, unlocking new avenues for VTON and size estimation.
- **Baseline benchmarks** for virtual try-on, cloth size estimation and novel view synthesis.

2. Related work

Progress in learning-based clothing reconstruction, simulation, and view synthesis depends on dataset realism and task alignment. Existing datasets can be grouped into those generated synthetically, those captured from the real world, and those tailored specifically for VTON applications.

2.1. Synthetic Datasets

Synthetic datasets are created using graphics engines [18, 22] and simulation tools [16], enabling scalable generation of massive volumes of data with perfect ground-truth semantic labels available by design [95]. Datasets like CLOTH3D and CLOTH4D [4, 95] are large-scale with rich data on garment dynamics, size, and fabric. BEDLAM [6] and BEDLAM2.0 [74] focuses on lifelike animated motion across body shapes and outfit types. Other specialized datasets, such as D-LAYERS [69] and ReSynth [53], focus on multi-layer clothing and point cloud representations respectively. However, these datasets suffer from a realism gap, struggling to model complex human appearance, motion, and clothing deformation. Even photorealistic attempts [6] fail to precisely capture the dynamics of real-world garments.

2.2. Real-World Datasets

To capture authentic clothing dynamics and appearance, many researchers employ multi-view volumetric capture systems [17, 34] to record clothed humans. These datasets vary significantly in scale, fidelity, and the types of data and annotations. For a direct comparison, refer to Tab. 1a.

Foundational and Large-Scale Datasets such as Human3.6M [29] and CMU Panoptic Studio [34] are established benchmarks for large-scale human capture. Human3.6M provides 3.6 million 3D poses [29], while CMU

Panoptic Studio utilizes a massive camera array for capturing social interactions [34]. More recent large-scale efforts include HuMMan [7], which offers multi-modal data for 1,000 subjects with a focus on versatile sensing and modeling. DNA-Rendering [11] increases diversity by featuring 500 subjects/1,500 outfits captured by a multi-camera setup. Currently, the largest dataset by frame count, MVHuman-Net++ [41], provides 645 million frames from 4,500 subjects in daily dressing, incorporating enhanced annotations such as pseudo normal and depth maps. Some clothing-specific large-scale datasets include 4D-DRESS [79], a 4D dataset with high-quality textured scans accompanied by vertex-level semantic annotations and segmented garment meshes for 64 outfits/520 sequences. SIZER [75] focuses specifically on garment fitting and sizing, capturing 100 diverse subjects. Similarly, X-Humans [71] and 4DHumanOutfit [2] provide clothed scans but lack the depth of semantic annotations and sizing variations.

Despite their impressive scale, these datasets have limitations for fashion-centric applications. They lack fine-grained semantic garment annotations, material data, and paired catalogue images. Furthermore, the resources required for processing this immense volume of data are substantial, restricting their accessibility for constrained setups.

High-Fidelity and Specialised Datasets prioritize high-quality capture for specific applications. Examples include ActorsHQ [30] for novel view synthesis, UltraStage [92] for relighting, AIST++ [43] with paired music and 3D dance motion, Hi4D [85] with human-human interaction, and FreeMan [78], collected entirely “in-the-wild” using synchronized smartphone cameras. While these datasets offer unique features or high-quality data, their applicability is limited for general-purpose research.

2.3. Fashion and Virtual Try-On Datasets

Datasets for fashion analysis and VTON vary significantly in dimensionality and in the availability of paired data, i.e. the explicit link between a garment’s catalogue (product) image and its worn (on-person) state. This pairing is crucial for VTON [12]. Existing works, also shown in Tab. 1b, fall into the following distinct categories: (1) *Unpaired 2D datasets* are foundational, large-scale 2D image collections used for recognition, retrieval, and parsing. However, they lack the paired images needed for VTON. This category includes DeepFashion [49], DeepFashion2 [25], Fashionista [83], Fashion-Gen [68], and FashionPedia [31]. (2) *Paired 2D datasets* provide the paired catalogue-to-worn images essential for VTON synthesis but lack 3D geometric information, for example, the standard single-pose datasets VITON [26] and VITON-HD [12]. Datasets like Dress Code [57], IGPair [70], MVG [77], MPV [19], LookBook [86], FashionOn [28], and FashionTryOn [89], further use multi-pose setup with 2 to 8 different poses per sub-

ject. VVT [20], TikTokDress [59], and ViViD [23] capture subjects in motion from a single video. Despite their diversity, these datasets lack the synchronized multi-view data to unlock novel approaches. (3) *3D/4D geometric* datasets provide crucial shape and dynamics information. Examples include 3D datasets like DeepFashion3D [94], GarVerseLOD [52], and CloSe-D [1], and dynamic 4D datasets like Thuman 4.0 [91], 4D-DRESS [79], and 4DHumanOutfit [2]. While invaluable for shape and motion analysis, their lack of paired data restricts their use in VTON.

Overall, the field lacks a dataset that bridges the gap between VTON and multi-view capture. VTON-focused datasets [12, 57, 70] are 2D-limited, while 4D geometric ones [75, 79] lack the necessary catalogue-to-worn pairings. Existing real-world capture methods often require resource-heavy setups [30], and few datasets adequately include complex, unexplored scenarios like multi-layering or diverse styling. We therefore introduce MV-Fashion, providing an accessible, multi-view dataset that explicitly links multi-view video data of complex styling with static catalogue images to jointly address garment dynamics, size estimation, and virtual try-on.

3. MV-Fashion

This section provides an overview of MV-Fashion, outlining the data acquisition setup and protocol, summarizing relevant statistics, and describing the high-quality annotations designed to facilitate downstream applications.

3.1. Dataset Acquisition

Setup. The acquisition setup is built upon a custom hybrid multi-view capture system, utilizing accessible and readily available hardware. Specifically, we use 60 Raspberry Pi global shutter cameras (1.6 MP), and 8 Orbbec Femto Bolt cameras to provide complementary depth and 4K video streams. The cameras are mounted in three rows on a 20-sided aluminium frame to provide dense coverage around the subject. To ensure precise temporal alignment, all cameras operate under an external electronic synchronization, achieving a frame alignment of less than 2 milliseconds across all cameras. The controlled illumination setup, consisting of 40 high-power LED panels, ensures consistent lighting and allows for low exposure times to mitigate motion blur during sequence recording. Fig. 1 illustrates the capture setup and shows representative examples of recorded subjects and outfits.

Collection Protocol. Our recording protocol defines three sequence types, each recorded as a 20-second video at 15 fps: (1) *Body sequence* serves as a baseline, capturing the subject in minimal clothing performing fixed, canonical poses for body-shape estimation. (2) *Template sequence* captures the static geometry of each outfit using the same fixed poses. (3) *Motion sequence* captures the subject per-

forming five randomly selected fashion-oriented poses to model dynamic garment behavior. To acquire rich garment details and variety, we record multiple motion sequences for each outfit. This process includes capturing different styling variations when possible, as well as multi-layer scenarios where new garments are added. To complement the visual data, we record garment measurements, material data, and other metadata, as described in Sec. 3.3. Additional technical details about the capture setup and recording protocols are provided in the Suppl. Sec. 8.

Ethics Considerations. The data collection was reviewed and approved by the authors’ university data ethics board, and all participants provided written informed consent prior to the study. Although we aimed to collect a balanced dataset, geographical constraints led to a dominance of European and American participants, which may bias both the data and the derived baselines. Consequently, any models trained on MV-Fashion may encode inherent biases related to underrepresented ethnicities, cultural backgrounds, clothing norms or fashion trends, or they might not generalize well for different populations.

3.2. Dataset Statistics

The data collection process systematically captures a wide range of human dynamics and appearances, featuring video recordings of 80 subjects performing diverse dynamic actions. This cohort has a gender distribution of 50.6% male, 45.7% female, and 3.7% non-binary. The subjects’ origins are primarily Europe (56.8%), followed by South America (28.4%), North America (9.9%), and Asia (4.9%).

Each subject is recorded in 3 to 10 different outfits, encompassing multiple garment types, including challenging configurations with multiple layers of clothing. The resulting dataset comprises 3,273 video sequences. In total, there are 474 sets of outfits, constituted by 754 individual pieces of garments, resulting in a total volume of 72.5 million frames. Out of these 474 outfits, 326 have a single layer of clothing, 145 have two layers, and there are 3 cases with three layers. Tab. 2 reports the distribution of garment categories in the dataset, including their frequency in layered and styled outfits.

	shirt	blouse	pants	shorts	dress	jacket	sweater	sweatshirt	skirt	coat	jumpsuit	vest	cardigan	blazer	tights	stockings
Total	38.3	21.2	11.7	5.2	5.1	3.8	3.6	3.4	3.0	1.3	1.1	0.9	0.7	0.1		
Layer	51.6	0.0	0.0	33.3	97.4	82.1	81.5	0.0	100	70.0	100	100	100	100	0.0	
Style	7.7	0.0	0.0	0.0	86.8	39.2	55.5	0.0	59.1	10.0	62.5	28.6	60.0	0.0		

Table 2. This table shows the distribution of different clothing categories across the dataset (Total). It also shows how often each clothing type shows up in multi-layered outfits (Layer) or in outfits with style variations (Style). All values are percentages.



Figure 2. Available data for one subject in a single clothing set. (a) *Subject*: Frontal view, clothing layers (w & w/o jacket), styles (open & closed jacket) and template recordings, four representative RGB views, and depth images with the reconstructed point cloud. (b) *Image Annotations*: Foreground segmentation isolating the subject, garment segmentation for each clothing item, fitted SMPL-X body model, and labelled bounding boxes for all garments in each frame. (c) *Garments, Materials & Sizing*: For each garment, frontal and back views in stretched and normal states, text description of the clothing, sizing chart with corresponding measurements (in centimeters), and properties.

3.3. Dataset Annotation

Annotation Pipelines. Our dataset curation process includes camera calibration, pixel-level segmentation, 3D point cloud reconstruction, and 3D body model annotation. We first calibrate camera intrinsics, distortion, and extrinsics using AprilTags [15, 60], perform stereo calibration between RGB and depth sensors, refine depth alignment with ColorICP [61] into a 3D point cloud, and adjust colors using polynomial correction [24]. We then generate foreground and layered garment masks using a unified two-stage pipeline, employing initializers like YOLOv8 [76] and the semantics-aware Qwen3-VL [65], followed by segmentation with SAM2 [66], and manual quality checks. Finally, we annotate body pose and shape using the SMPL-X [63] model by detecting 2D keypoints with RTMW-x [32], triangulating them to 3D using the calibrated camera parameters, and optimizing SMPL-X parameters via a modified SMPLify-X [63] pipeline that incorporates point cloud data for better shape fitting on the minimally clothed scans.

Garment Attributes. Garment sizing charts are standard tools for clothes designers and online shops for assigning labels like S, M, and L to clothes and determine their fit. To the best of our knowledge, there is no public dataset providing detailed sizing charts for clothes. In MV-Fashion, we provide (1) 14 clothes category labels, (2) detailed sizing charts computed with a measuring tape, (3) fitting appearance of the clothes on subjects as categorical labels, (4) draping styles, (5) materials and elasticity, and (6) detailed clothes descriptions computed by large language models.

To standardize the analysis of the sizing charts, we combine the clothes categories into six groups based on the specific body parts measured: **G1** (shirt-blouse), **G2** (pants,

shorts, tights-stockings), **G3** (skirt), **G4** (jacket, sweater, sweatshirt, coat, vest, cardigan, blazer), **G5** (jumpsuit), and **G6** (dress). Beyond numerical measurements, we also annotate the garments based on their fitting appearance on the person with three categories: (1) slim with a tight fit, (2) regular, and (3) loose with an oversized look. We enrich our data by categorizing the styles into groups such as rolled-up sleeves, fully/partially closed jackets, and tucked-in shirts. Additionally, we annotate physical properties by manually extracting the garment material (e.g., denim, cotton) and estimating elasticity on a discrete scale ranging from 1 (rigid) to 5 (highly stretchable). Finally, we include textual descriptions for each item, generated by applying Qwen3-VL [65] to the frontal and back garment images.

For examples of the available data and its annotations, please refer to Fig. 2. For more technical details, discussions, and further examples, see Suppl. Sec. 9.

4. Baselines

4.1. Virtual Try-On

Latest image-based VTON approaches [13, 14, 38, 82, 93] strongly rely on single-view datasets [12, 57], limiting progress toward fine-grained controllability and multi-view virtual try-on. MV-Fashion bridges this limitation by providing a rich dataset, as stated in Sec. 3, enabling conditioning signals far beyond conventional single-view settings.

To assess its applicability, we employ two state-of-the-art VTON approaches, diffusion based IDM-VTON [13] and flow matching based InsertAnything [72]. Specifically, we design three baseline experiments to evaluate both compatibility with existing VTON pipelines and the novel capa-

bilities enabled by our dataset: (1) Single-View, (2) Semantic Controllability, and (3) Multi-View Geometric Analysis. *Single-View Baselines:* We train both models on a frontal-paired subset replicating well-established single-view settings [12, 57]. *Semantic Controllability:* We extend IDM-VTON by augmenting the input prompt using a text template based on our categorical draping styles (e.g. *base garment is invisible, outerwear is fully closed, stretched sleeves, untucked, hood down*). This tests the augmented model’s semantic alignment with appearance change instructions at test time by comparing no-style versus styling prompts. *Multi-View Geometric Analysis:* We design a two-part geometric benchmark using a subset of synchronized views to quantify cross-view consistency. This benchmark utilizes a mixed subset of person views (frontal and rear target poses) for both experiments. The first *Cross-View Geometric Test* directly quantifies IDM-VTON limitations under cross-perspective geometric mismatch by requiring it to synthesize the target pose’s appearance using only the frontal garment catalogue image, while in the second experiment, we validate our dataset’s capacity for *View-Adaptive Try-On*. In the latter case, we extend IDM-VTON to utilize both frontal and rear garment catalogue images, passing them to a shared IP-Adapter module [84]. This design allows the model to select the most geometrically compatible conditioning view for each target pose.

4.2. Size Estimation

Inferring accurate garment measurements from images of clothed humans is a challenging and largely unexplored task due to distortions from arbitrary poses, drapes, and wrinkles. To date, most works have focused on automatic garment size estimation from controlled, frontal 2D images, often by detecting keypoints on the normalized item [40, 62]. A more robust alternative is to infer the 2D sewing pattern ([9]), which provides clothing’s direct measurements. This is not limited to garment images; clothed humans [44, 47] and even text guidance [5] can also be used. Taking all that into account, we leverage our data to predict garment size measurements directly from images of clothed individuals.

Our approach adapts SPnet [45], a recent model designed to predict sewing parameters from posed people, in which an encoder-decoder network $\Psi(G^s, P^s, P^t)$ is used to predict the target garment normal image G^t in a canonical pose, where G^s , P^s and P^t are image representations for the input garment normal, input body pose, and output canonical pose, respectively. Then, a separate network $\Phi(G^t)$ is trained to estimate the sewing parameters. We refer the reader to [45] for the original architecture details. Given motion sequences, we obtain G^s with our segmentation and Sapiens [37], and P^s from our SMPL-X estimation. Likewise, G^t and P^t are computed from the template recordings. This allows us to train on our real data rather than the

synthetic one used in SPnet.

We follow the same architecture and training protocol as SPnet for the network Ψ . However, we update Φ to regress normalized garment sizes, scaled to $[0, 1]$ via dividing by the maximum size in the dataset. We evaluate three variants of Φ : (1) individual models trained per garment group (Sec. 3.3), as in SPnet; (2) a single multi-task model trained jointly on all groups; and (3) a multi-task model where the SegNet [3] encoder in (2) is replaced with SwinV2 [50] and additionally conditioned on P^t , to better align garment regions with the corresponding sizing chart entries.

4.3. Novel View Synthesis (NVS)

Novel View Synthesis is a critical component of modern virtual try-on and digital fashion applications, enabling the creation of realistic, 360-degree views of clothed individuals. Recent state-of-the-art methods for clothed human reconstruction [42], garment generation [67], and 3D virtual try-on [8] increasingly rely on NVS techniques to handle complex clothing deformations and textures. Therefore, to validate our dataset’s suitability for these advanced applications, we benchmark its performance using popular NVS methods. We select three models implemented within the Nerfstudio framework [73]: Instant-NGP [58], Nerfacto, and 3D Gaussian Splatting (splatfacto) [36].

Our investigation is two-fold. First, we conduct a comparative analysis of these three methods on MV-Fashion to establish baseline NVS performance. Then, we perform an ablation study on the number of input views to measure the effect of view density on reconstruction quality.

For more details on the baselines, see Suppl. Sec. 10.

5. Experiments

In this section, we outline the data, training protocols, and evaluation metrics, as well as discuss the baseline results.

5.1. Virtual Try-On

Data and Training Protocols. We utilize a subject-based split for all VTON experiments, reserving 10% of subjects as the test set. For the Frontal Single-View Subset, we sample i.i.d. from sequences captured across seven distinct frontal-facing camera angles to ensure view diversity. This subset totals 15,803 training images and 2,188 testing images. The Multi-View Subset incorporates images from seven additional rear-facing cameras for cross-perspective challenges, totaling 14,689 training images and 2,073 testing images. Experiments rely on implementations of IDM-VTON [13] and InsertAnything [72], using their standard training protocols with modifications described in Sec. 4.1.

Evaluation Metrics. We report three standard VTON metrics: SSIM [80], LPIPS [88], and FID [27].

Results. Quantitative results for the *Single-View Baseline* (Tab. 3) show that the frontal-paired subset of MV-

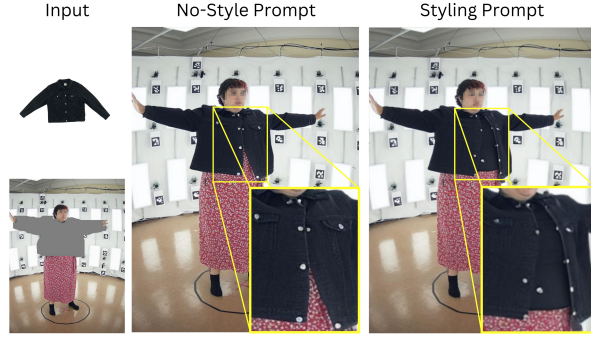


Figure 3. Qualitative comparison showing models trained with styling-augmented data respond to fine-grained styling prompts (*a jacket, the outer wear is fully open*), producing outputs that are sometimes distinguishable from no-style prompts (*a jacket*).

Fashion can be directly used with existing VTON pipelines. Both IDM-VTON and InsertAnything achieve high-fidelity scores on all metrics. The capacity to control try-on results based on styling annotations (*Semantic Controllability*) presents a potential further research directions. As illustrated in Fig. 3, IDM-VTON trained with augmented prompt data demonstrates the ability to react to the specific instruction within the styling augmented prompt, a capability absent in the model pre-trained on the VITON-HD dataset. However, we found that the model often struggles to follow these additional semantic signals outside its primary guidance (*e.g.*, from IP-Adapter). Even in successful control cases, subtle artifacts remain present, demonstrating that achieving fine-grained styling control is currently a highly challenging task.

For Multi-View Geometric Analysis, the *Cross-View Geometric Test* reveals a performance drop across all metrics (Tab. 3), directly quantifying the difficulty models face in maintaining geometric consistency under cross-perspective constraints. The *View-Adaptive Try-On*, conversely, shows a partial reduction in failure cases when models adaptively use both frontal and rear garment views (Fig. 4), validating the research potential enabled by these multi-view pairs.

Since new architectural design is outside our scope, the development of advanced control mechanisms and multi-view models is left as a valuable future investigation.

Benchmark	Experiment	SSIM $\uparrow$	LPIPS $\downarrow$	FID $\downarrow$
Single-View	IDM-VTON [13]	0.881	0.086	10.187
	InsertAnything [72]	0.927	0.065	8.192
Multi-View (IDM-VTON)	Cross-view	0.868	0.098	12.907
	View-adaptive	0.873	0.093	12.775

Table 3. Quantitative results benchmarking Single-View Baselines and Multi-View Geometric Analysis using the proposed MV-Fashion’s subsets described in Sec. 4.1.

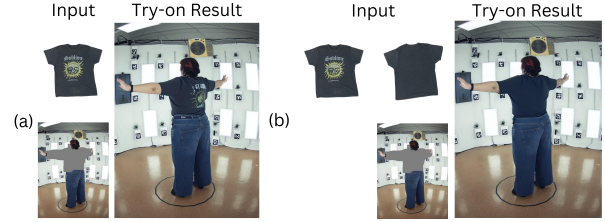


Figure 4. Results on (a) *Cross-View Geometric Test* vs (b) *View-Adaptive Try-On*. The updated IDM-VTON architecture can map between the catalogue view and the person’s pose when both front and rear images of the garment are provided to the model.

5.2. Size Estimation

Data and Training Protocols. We train Ψ and Φ independently, exclusively utilizing data from outer-layer garments to ensure full visibility, and without applying any data augmentation. For Ψ , we sample 30 uniformly distributed frames from five random frontal cameras per motion sequence to capture diverse poses. Each source tuple (P^s, G^s) is paired with the canonical configuration (P^t, G^t), derived from the initial frame of template sequences for the two most frontal views, yielding 300 training pairs for every outer-layer garment present in a sequence. For Φ , we use the 1,508 canonical G^t images paired directly with our annotated measurements. All versions of Φ are trained 5 times and the results are averaged to avoid randomness effect. The test split follows Sec. 5.1, ensuring strict separation between train and test subjects.

Evaluation Metrics. We report two metrics for Ψ : MAE to measure pixel-level accuracy, and SSIM for perceptual quality. For the size predictor (Φ), we also provide MAE, in centimeters, along with its standard deviation.

Results and Analysis. Qualitative results for Ψ (Fig. 5) demonstrate effective disentanglement of pose from garment geometry, producing canonical, smoothed normals that recover the garment’s intrinsic shape even in challenging views. Quantitatively, Ψ achieves a global MAE of 0.0163 and SSIM of 0.9355, indicating high fidelity and structural preservation. For Φ , Tab. 4 validates the effectiveness of our multi-task approach (exploiting common measurements across garment groups) compared to the per-group training originally proposed in SPnet. The SwinV2-based model with P^t guidance yields the most robust performance, achieving the lowest MAE (4.279 cm). These baselines demonstrate that MV-Fashion contains sufficient signal to learn accurate sizing from real-world images.

5.3. Novel View Synthesis Benchmarking

Data and Training Protocols. We sample one random static frame from all subjects to capture data diversity. All methods are trained and evaluated independently on these scenes, with their average as the reported result. For com-

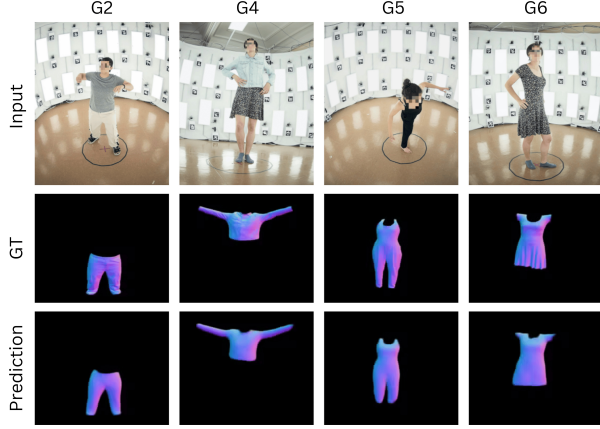


Figure 5. Qualitative results of the canonical garment normal predictor Ψ for groups G2, G4, G5 and G6; showing input frame, ground truth (G^t), and the predicted normal image.

Group	Per-Group	Multi-Task	Multi-Task + SwinV2
G1	4.069 (5.861)	4.361 (6.061)	3.933 (5.994)
G2	3.006 (2.541)	3.185 (2.619)	3.067 (2.762)
G3	9.951 (8.437)	6.847 (9.174)	6.643 (10.135)
G4	5.092 (7.377)	5.644 (8.563)	4.436 (6.537)
G5	12.109 (10.313)	4.295 (2.746)	4.889 (4.633)
G6	7.767 (7.954)	6.549 (7.234)	6.389 (6.562)
Average	4.904 (6.533)	4.710 (6.392)	4.279 (5.870)

Table 4. MAE results (cm) for the size predictor Φ , reported as mean (std). We compare the three variants from Sec. 4.2 across all garment groups (defined in Sec. 3.3) and the average.

Method	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$
instant-ngp [58]	29.120 (1.555)	0.936 (0.015)	0.089 (0.022)
nerfacto [73]	26.535 (2.047)	0.952 (0.011)	0.052 (0.009)
splatfacto [36]			
4 views	24.633 (2.230)	0.933 (0.015)	0.074 (0.019)
8 views	27.299 (1.850)	0.944 (0.013)	0.050 (0.012)
16 views	28.500 (1.709)	0.949 (0.013)	0.039 (0.008)
32 views	29.211 (1.764)	0.954 (0.013)	0.032 (0.007)
56 views	29.567 (1.877)	0.957 (0.013)	0.028 (0.006)

Table 5. Comparison of image quality metrics as mean (std). We compare against other methods and provide an ablation study on the number of views for splatfacto.

patibility across methods, we only use the 60 main cameras, excluding the 4K cameras. Our primary experiment uses a 56/4 train/test split, with test views selected from challenging viewpoints (e.g. top-side angle). A second experiment ablates the number of training views (e.g., 56, 32, 16, 8, 4) to evaluate the impact of view density. To prevent a proximity bias between the train and test views, the training split is randomized for each scene.

Evaluation Metrics. We report three standard NVS metrics: PSNR, SSIM [80], and LPIPS [88].

Results and Analysis. Quantitative results (Tab. 5) confirm that all benchmarked methods achieve high-fidelity reconstructions, validating our dataset’s suitability for NVS

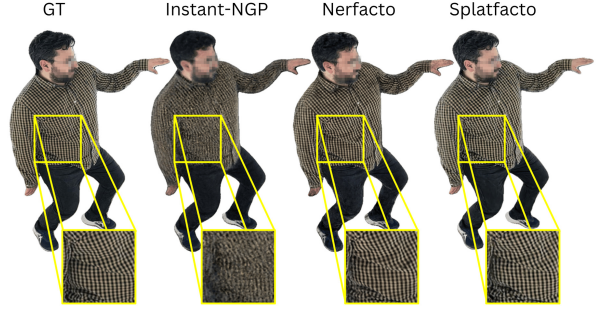


Figure 6. Qualitative examples of the presented NVS methods. It shows how Nerf-based methods struggle with fine details, but Gaussian Splatting can reconstruct fine textures and the wrinkles.

research. Qualitative results (Fig. 6) further show that the methods can reproduce intricate garment details such as fine textures and wrinkles. Our view-density ablation (Tab. 5) with the splatfacto method shows that all metrics improve with more training views, but performance saturates at 56 views. This suggests that adding more cameras to the system would only provide diminishing returns, demonstrating that our multi-view setup is appropriate for this task.

The results collectively validate MV-Fashion as a robust testbed for photometric, geometric, and semantic consistency across fashion-centric tasks. For more baseline results and discussions, see Suppl. Sec. 11.

6. Conclusion

We introduced MV-Fashion, a comprehensive multi-view video dataset designed specifically for fashion-centric applications. The dataset offers extensive real-world garment diversity, rich annotations, and paired multi-view captures that support key tasks such as Virtual Try-On, size estimation, and novel view synthesis. We also established benchmark evaluations using state-of-the-art methods to provide a foundation for future research. To promote reproducibility and community-driven progress, both the MV-Fashion dataset and baseline implementations will be publicly released upon publication. We believe MV-Fashion will serve as a valuable resource and catalyst for advancing research in fashion understanding and digital human modeling.

Limitations and Future Works. We provide several types of annotations and the data used for our baseline models. Most annotations are generated using off-the-shelf, well-established methods complemented by targeted manual QA; we therefore focus our evaluation on downstream task performance rather than exhaustively benchmarking every intermediate annotation, and encourage future work to further analyze and improve these components. We report baselines for the most common downstream tasks, but the dataset is not limited to these. It can also support tasks such as instance segmentation or garment classification.

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