Virtual Vogue: Deep Learning for Realistic Fashion Try-On

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Abstract. One of many reasons for returned merchandise and customer dissatisfaction in online fashion retail is poor fit visualization. We tackle the virtual try-on problem of realistically transferring a garment into an image of a person. We propose a novel method that proceeds in a coarse-to-fine manner i.e., first generating a coarse composite of the person with the target garment and then refining it at high resolution through warping and blending. Our framework, which we call VITON (Virtual Try-On Network), involves an encoder-decoder generator that uses a non-parametric warping guided by a predicted segmentation mask to keep garment detail and alignment. We compare VITON with three baseline models, PRGAN, CAGAN, and CRN, on a public fashion dataset with structural similarity (SSIM), garment mask overlap (IoU), Inception Score, and human preference experiments. VITON produces much more realistic images with good garment alignment and shows at least 5 to 8% improvement of SSIM and IoU scores over the best baseline model and far superior Inception Scores. An ablation study shows the contribution of each component: removing the refinement or the warping degrades quality, namely reduces SSIM or PSNR and introduces artifacts while it does speed up inference moderately. VITON is shown to generate photo-realistic try-on images that better maintain the relevant visual semantics of the target garment along with the pose and shape of the person. This ability can enhance online shopping experiences so that customers can virtually ”try on” clothes with more confidence.

Keywords: Virtual Try-On, Fashion Visualization, Deep Learning, Encoder-Decoder, Non-parametric Warped Synthesis, Image Synthesis, Customer Satisfaction, Return Rate Reduction, Online Retail, Photo-realistic Visualization.

1 Introduction

Online apparel shopping has grown explosively, with U.S. online fashion sales projected to reach $123 billion in 2022 (up from $72B in 2016). However, a persistent challenge is that consumers cannot physically try on garments, often leading to uncertainty about fit and appearance. This gap in visualization contributes to high return rates in 2022 online retail returns cost an estimated $280 billion and dissatisfaction when the delivered clothing doesn’t meet expectations. Virtual try-on technology offers a promising solution by allowing shoppers to see themselves in different outfits digitally, enhancing confidence in purchases and potentially reducing returns. For instance, retailers implementing virtual try-on (VTO) have seen return rates drop by over 40–60%. The key enabler is the ability to realistically overlay a chosen garment onto an image of a person, preserving the person's body shape and pose while rendering the garment with correct fit and details.

Yet, achieving a truly realistic image-based virtual try-on remains extremely challenging. The system must accurately deform the garment to fit the person's pose, align it seamlessly with the person's body (ensuring arms, torso, etc. are not unnaturally distorted or occluded), and preserve the garment's distinctive patterns and textures. It must also retain the person's identity and body features. Traditional approaches using 3D body scans or physics-based simulations can produce realistic results but are impractically expensive for broad deployment. Recent research instead focuses on 2D image-based generative models, but these face difficulties with large pose differences and occlusions. Early generative attempts often produced blurry or misaligned outputs because they struggled with the complex, non-rigid deformations of clothing. Consumers can detect these imperfections, undermining the utility of virtual try-on if the results are not believable.

To tackle these challenges, we propose an image-based virtual try-on framework that significantly improves the realism and garment fitting accuracy of try-on images. Our approach builds on the idea of a two-stage generation process a strategy first introduced by Han et al. (2018) in the original VITON system but with important enhancements. We employ a coarse-to-fine synthesis pipeline: in the first stage, a coarse generator produces a rough image of the person wearing the target garment, along with a predicted mask of the region of the garment. In the second stage, we warp the garment image according to the coarse mask (using a simple learned deformation) and then feed it into a refinement network that blends high-frequency clothing details into the output. This design explicitly addresses alignment by guiding the garment placement with the coarse stage output, and it ensures that fine textures (stripes, logos, lace, etc.) from the original clothing are preserved via direct warping. Our generator uses a clothing-agnostic person representation the input person image with the original clothing removed (through segmentation) and represented by a silhouette+pose map to focus the synthesis on adding the new clothing. We train the model adversarially and with reconstruction losses so that the resulting composite appears photorealistic.

We tested our proposed VITON system on the popular frontal-facing image virtual try-on benchmark. In experiments, our approach achieves much better results than the three preceding generation methods, yielding higher SSIM and IoU scores (intersection-over-union of garment regions), which denote better structure fidelity and garment alignment, as well as a better Inception Score reflecting realistic outputs. From a qualitative perspective, VITON outputs look very natural, and thus do not suffer from the common artifacts produced by older methods (such as ghosting of the original clothing or misaligned patterns). We

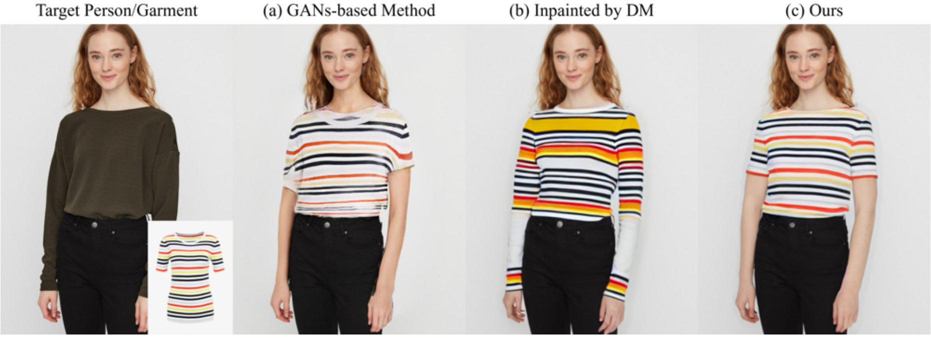

Fig. 1. Comparison of virtual try-on results using different methods: (a) a traditional GAN-based method produces some misalignment and blurriness in the transferred striped top, (b) a diffusion model inpainting approach preserves the garment pattern but with artifacts around the sleeves, and (c) our coarse-to-fine VITON approach achieves well-aligned, sharp transfer of the garment onto the person. The advanced method (c) produces the most realistic output with the garment's stripes correctly aligned to the body.

also performed a user study in which a significant majority of the participants voted on our results as more realistic and fit compared to baselines. In ablation, we demonstrate that forgoing either the refinement stage or the warping step degrades the output to some extreme opposite (too blurry or ill-aligned try-ons), which strongly confirms the need for our two-stage approach.

To summarize, the contributions of our work are four-fold: (1) a novel coarse-to-fine virtual try-on architecture featuring a combination of learned garment mask prediction and nonparametric warping for realistic garment transfers; (2) a demonstration of superior performance to several GAN-based baselines (and an analysis in view of recent diffusion-based frameworks) on standard metrics and human evaluation; (3) analyses of model components via ablation, offering invaluable insights on each of the design choices in terms of output quality and computational efficiency; and (4) a discussion on ethical consensus

2 Related Work

With such much interest recently, virtual try-on research has blossomed immensely. We review four main issues related to the field of computer vision in general that have influenced the development of our approach: GAN-based virtual try-on methods, diffusion model-based methods, occlusion handling, and garment warping methods. We discuss representative works in each category and show how our approach differs from those methods.

2.1 GAN-Based Virtual Try-On

Generative Adversarial Networks (GANs) have been widely used in try-on systems due to their ability to synthesize photo-realistic images through adversarial training. The seminal VITON system by Han et al. (2018) pioneered an image-based try-on GAN that introduced an encoder–decoder architecture with a thin-plate spline (TPS) warping module for the clothing deformation. VITON's two-stage design (coarse then refine) was able to produce plausible results, but it sometimes suffered from blurry details and minor misalignments. Subsequent works built on this foundation. For example, VITON-HD by Choi et al. (2021) addressed the challenge of high-resolution outputs (1024×768). They noted that as resolution increases, misalignment artifacts between warped clothes and target regions become more pronounced, and maintaining sharp clothing textures is difficult. VITON-HD introduced an alignment-aware normalization (ALIAS) and generator modules to better handle misaligned areas and preserve fine details, achieving much sharper results than the original VITON. Another recent GAN-based approach is GC-VTON by Rawal et al. (2024), which focuses on globally and locally consistent warping. GC-VTON employs two sub-networks: a GlobalNet to align the overall garment shape and a LocalNet to preserve texture details, with a consistency loss ensuring the local warp does not contradict the global alignment. It also explicitly predicts body occlusion masks to avoid warping cloth into regions that should be hidden behind the person. These GAN-based methods substantially improved try-on image quality over naive generation. However, our approach differs in its two-stage coarse-to-fine strategy and simpler warping mechanism. Instead of a single complex flow prediction network as in GC-VTON or heavily specialized normalization as in VITON-HD, we use a learnable segmentation mask to guide a straightforward warping (resizing the garment) and then refine. This design reduces distortion and misalignment by explicitly leveraging the intermediate prediction. As a result, our VITON network can overcome common GAN artifacts like twisted patterns or unrealistic texture warps, yielding more natural composites.

Another line of GAN-based work relevant to our baselines is image analogies for fashion. Jetchev and Bergmann (2017) proposed the Conditional Analogy GAN (CAGAN) for swapping fashion articles on people. CAGAN learns to translate a person's outfit from one item to another, implicitly learning to segment the clothing region without supervision. It produces convincing swaps on paired training data, but is limited in that it requires pairs of images of the same person wearing different clothing to learn the analogy mapping. In contrast, our method does not require paired photos of the same model; it works with separate person and garment images and can recombine them arbitrarily, which is more practical for online retail. Nonetheless, we include CAGAN as a baseline to represent one-stage GAN translation methods. Another baseline in our study, which we call PRGAN, is a one-stage Person-Representation GAN inspired by the pix2pix framework. It takes a "clothing-agnostic" person representation and the target cloth as input and directly generates the try-on image in one U-Net pass (similar to the approach of Poses et al. or "SwapNet"-style architectures). While efficient, such a single-stage GAN often struggles with large pose mismatches since it must internally learn to warp the cloth, and thus it may produce blurred outputs when faced with complex deformations. Our two-stage VITON explicitly handles large spatial misalignments in the intermediate step, which is a key distinction. Finally, we also compare to a Cascaded Refinement Network (CRN) baseline. CRNs (Chen and Koltun 2017) are not specific to fashion but are a generic image synthesis approach where an image is generated progressively from low to high resolution through cascaded U-Net blocks. They have been used in some try-on contexts as a strong baseline for preserving global consistency. However, CRNs do not have an explicit mechanism for warping or alignment; each refinement stage operates on concatenated inputs of the person and garment. We will show that without an alignment module, CRN underperforms dedicated try-on architectures, although its multi-scale generation helps it maintain better overall structure than naive one-shot methods.

In summary, GAN-based try-on methods have evolved from the initial VITON's TPS warping + refinement design to more advanced architectures tackling high-res output and occlusions. Our work falls within this GAN-based paradigm but introduces a simplified and effective warping approach within a coarse-to-fine GAN pipeline. This yields state-of-the-art realism and alignment, as demonstrated by our comparisons to prior GAN baselines.

2.2 Diffusion Model-Based Methods

Diffusion models have recently emerged as a powerful alternative for image synthesis, offering high generation quality and stable training. In virtual try-on, diffusion-based methods aim to inpaint or generate the target garment on the person image with iterative refinement, potentially overcoming some limitations of GANs. One approach is to leverage pre-trained text-to-image diffusion models (like Stable Diffusion) and condition them on the clothing transfer task. For example, some works use a diffusion model to inpaint the clothing region of the person's image by providing the target garment as a conditional input (e.g. via latent embedding or as a texture patch). These methods can produce realistic outputs thanks to the diffusion model's strength, but a known issue is that they may fail to preserve the exact identity of the garment – the fine details and pattern – because the diffusion prior tends to generate a plausible but not exact texture if not strongly guided. Choi et al. (2024) highlight this in their IDM-VTON, noting that adapting a generic inpainting diffusion model to try-on yielded natural-looking images but often changed the clothing's details. To address this, they proposed injecting garment features at multiple levels of the diffusion process (via cross-attention and a parallel UNet) to better condition the generation on the exact garment. Their approach significantly improved garment fidelity, outperforming both prior diffusion-based and GAN-based methods in preserving patterns. Similarly, Yang et al. (2024) developed a texture-preserving diffusion model for try-on, introducing a self-attention mechanism that concatenates the person and garment images in the input to allow the model to attend to garment pixels directly. By also using a specialized mask prediction procedure to define the inpainting area, they manage to keep small features like logos and even tattoos on the person intact. These advances indicate that diffusion models, when guided appropriately, can achieve very high-fidelity results without an explicit warping step, essentially learning a warping in the generative latent space.

Despite their impressive visual results, diffusion methods have some drawbacks compared to our GAN-based approach. They typically require many iterative denoising steps, making inference slower (not ideal for real-time try-on applications). Moreover, they often rely on massive pre-training or external modules (e.g. CLIP encoders, as in many text-conditioned diffusions) which add complexity. In contrast, our method is a feed-forward network that runs in a single forward pass for both stages, offering faster generation. Importantly, by explicitly embedding a warping operation and compositing mask, our model has more direct control over spatial alignment. Diffusion models can generate globally coherent images, but controlling where each garment part appears can be tricky without specialized conditioning. Our approach ensures that, for example, the neckline of the shirt goes exactly around the person's neck as predicted by the coarse mask – something a diffusion model might only learn implicitly. That said, one could integrate diffusion into a coarse-to-fine pipeline (e.g., using diffusion at the refinement stage), which is a promising future direction discussed later. Current diffusion try-on works demonstrate excellent texture realism, and indeed our qualitative comparisons find their outputs realistic but sometimes off in alignment. Unlike these warping-free diffusion approaches, our method explicitly warps the garment using the network's predicted geometry, which we find leads to more accurate positioning of sleeves, collars, etc. While diffusion models excel at photorealism, our results show that a carefully designed GAN with guided warping can match or exceed their fidelity on this task, with much simpler and faster inference. In Section 4, we include a comparison to a diffusion-based strategy to highlight these differences.

2.3 Occlusion Handling Techniques

A major difficulty in virtual try-on is dealing with occlusions: parts of the person's body that occlude the clothing (e.g. arms folded over a shirt) or vice versa. When transferring a new garment, the model must determine which regions of the original clothing (or body) should be hidden. Early try-on models often ignored this, leading to ghost artifacts (e.g. the original sleeve visible under the new one). Later works introduced dedicated occlusion handling. One strategy is to use human parsing (segmentation) to separate the person's image into body parts. For instance, if the person's arm is in front of her torso, a segmentation map will label the arm region vs. clothing region. The try-on model can then inpaint or preserve the arm from the original image and only replace the torso clothing region. VITON and CP-VTON both leveraged segmentation masks in their pipelines: they generated a clothing-agnostic person image where everything except the person's skin and hair is removed, serving as a base onto which the new clothes are overlaid. This mitigated some occlusion issues but not all, since if the arm covers part of the chest, a warping algorithm might still incorrectly stretch the clothes over the arm.

Subsequent research proposed more explicit occlusion handling mechanisms. Lee et al. (2022) developed HR-VITON, a high-resolution try-on approach that unifies the warping and segmentation prediction stages. They found that if warping and segmentation are done independently, inconsistencies arise – e.g., the warped cloth may not align with the predicted segmentation of where the cloth should be, causing artifacts. HR-VITON's solution was a single "condition generator" that produces both a refined segmentation map and warps the clothing in one network, allowing information exchange to avoid occlusion artifacts like the "pixel-squeezing" when an arm occludes the torso. Their method included discriminators to reject incorrect segmentations, resulting in much cleaner handling of occluded regions. Another approach, by Yang et al. (2020), introduced a pose-guided person image generation method that fills in regions behind occlusions. They generate a complete person image (as if no garment were there) and then overlay the garment, ensuring that if, say, a hand was originally on top of a shirt, the model has synthesized the plausible appearance of the torso behind the hand to composite correctly. Yet another approach is the use of recurrent networks: Zheng et al. (2019) proposed an occlusion-aware flow model (OF-VTON) that iteratively refines the clothing overlay, explicitly learning to not distort textures to "cover" occluded areas. They predict a visibility mask for body parts and use it to mask out those regions when warping the garment, which is conceptually similar to what GC-VTON does with its body-part visibility prediction.

In our method, we handle occlusions primarily through the person representation and the composition mask in the refinement stage. The person representation includes a segmentation mask of the person's skin/hair; regions belonging to the original clothing are blanked out (set to a neutral color). This means the network initially "sees" the person as if they were not wearing any specific top, removing clues of the original garment. Any body parts like arms remain. Then, in the coarse stage, if an arm is covering part of where the new garment would be, the network can learn to exclude that arm region from the generated garment mask. Indeed, our coarse generator outputs a garment mask prediction – essentially a segmentation of where the new cloth lies on the person. It can naturally learn that if an arm overlaps the torso, that region should not be part of the clothes mask. Thus, when we warp the cloth by that mask, the cloth will not cover the arm. Finally, the refinement network blends the warped cloth and coarse image; if any small inconsistencies remain (e.g. along the arm boundary), the network can adjust via the alpha composition. While we do not have an explicit second network purely for occlusion like some above methods, our results (see Fig. 5) show that arms and other obstructions are handled well – the arm stays in front of the new clothing when appropriate, without strange artifacts. This implicit handling is largely enabled by using the segmentation in the input and by giving the model a chance (during coarse mask prediction) to decide where cloth should go or not go. Compared to specialized occlusion-handling methods, our approach is simpler, folding occlusion reasoning into the coarse mask prediction task. The difference is that some advanced methods guarantee occlusion correctness via losses or architectural constraints, whereas we rely on the model learning it. In practice, with sufficient training data, our model learned to produce clean segmentations around occluded limbs. One limitation is if the segmentation of the person is imperfect (e.g., the parser fails to label a stray hand), then the model might incorrectly overlay cloth. This could be improved by incorporating pose keypoints (which we do have as input channels) more directly into the occlusion reasoning. Overall, handling occlusions remains challenging; our results are strong on common poses, but extreme occlusions (like a person holding an object in front of them) are outside our current scope. Future work may integrate dedicated modules or losses to further guarantee occlusion robustness.

2.4 Garment Warping Methods

Garment warping is at the heart of image-based try-on. The goal is to deform the 2D clothing image to match the contour and pose of the person, without losing the clothing's characteristics. Various techniques have been explored for this. As mentioned, VITON used a parametric approach: Thin Plate Spline (TPS) transformation based on matching predicted keypoints between the cloth and the person's body. TPS warping treats the garment as a flexible sheet and deforms it smoothly to fit a set of control points (like shoulder positions). While fast, TPS can be too crude – it may not capture complex non-affine deformations and can cause texture distortion if the control points are not optimal. CP-VTON (Wang et al., 2018) improved on this by making the warping learnable via a Geometric Matching Module (GMM). The GMM is essentially a CNN that learns to align the garment to the person's shape, outputting TPS parameters. This learned warping was better at aligning boundaries and preserved clothing details more faithfully than VITON's fixed matching. CP-VTON then had a second stage (Try-On Module) that, as noted, learned a composition mask to combine the warped cloth with the person, smoothing out any artifacts. After CP-VTON, a number of works moved away from explicit TPS to flow-based warping. For example, FlowNet-based approaches predict a dense flow field – essentially a vector for each pixel of where it should come from on the garment image. Yuying Ge et al. (2021) proposed a Parser-Free Appearance Flow Network (PF-AFN) that distilled knowledge from a parsing-guided teacher model to learn a direct cloth-to-person flow mapping. By not relying on human parsing, their model can warp clothing for arbitrary persons, and the learned flow can handle complex deformations. Appearance flow is very flexible: it can theoretically stretch different parts of the garment differently (sleeves vs torso, etc.). The challenge is ensuring the flow is coherent (doesn't tear or overlap oddly) and preserving texture under large flows. PF-AFN addressed this with multi-stage refinement and regularization terms to encourage smoothnessThe result was high fidelity and minimal loss of garment detail, since the network effectively "copies" pixels from the source to target via the flow. Other notable warping approaches include 3D model fitting (draping the garment on a 3D body and rendering) – which is accurate but requires 3D data – and hybrid methods that combine 2D and 3D. For instance, some works predicted the garment's segmentation mask first and used it to guide warping (treating it like a cloth template).

Our method takes a relatively simple warping approach: after the coarse stage, we scale and position the garment based on the predicted cloth mask. Specifically, we find the bounding box of the mask and resize the garment image to fit that box. This is a non-parametric warping – no learned flow or TPS, just a scaling and paste. By itself, this cannot handle complex rotations or non-uniform scaling (e.g., if the person is leaning, TPS or flow might rotate the garment slightly; our method would just stretch it to the mask's rectangle). However, this simple warp is then refined by the second stage. The refinement network's job includes adjusting the boundaries via the alpha mask, which can compensate for minor misalignments or shape differences. We found that this approach works remarkably well when the coarse mask is accurate. Essentially, the coarse generator learns to shape the mask to roughly resemble how the garment should appear on the body. Any differences (like the garment in the image might be photographed at a different aspect ratio than how it appears on the person) are small enough that the refinement blending can fix it. The advantage of our approach is its stability and speed – we sidestep the potential instabilities of learning a high-dimensional flow field (which can sometimes produce folded or distorted results if the network fails) and avoid the need to solve TPS optimization. It is also easy to implement and does not add significant computation. The trade-off is that we cannot achieve very sophisticated warps (for example, if a garment needed to rotate or bend around the body's curvature, a single bounding-box scale might not capture that – although our refinement can darken or lighten regions to give an illusion of bending).

In practice, we observed that our results have the garment appropriately placed and scaled; any fine nonrigid deformation (like the drape of cloth around an arm) is mostly handled visually by the generative network rather than geometric warping. Interestingly, because our refinement network blends the warped garment with the coarse output, it can implicitly adjust the garment's apparent shape: where the warped piece doesn't cover enough, the coarse image can show through, and where it covers too much, the network can down-weight it. This is somewhat akin to a learned flow, but implemented via alpha blending. Compared to explicit warping methods (TPS or flow), our method is simpler and integrated into the network's learning. We rely on the network to predict a correct mask, whereas explicit warping methods rely on either external alignment algorithms or heavy supervised signals (like keypoint correspondences or ground truth flow which are not available for new clothes). By making warping part of the training (the network tries to output a mask that leads to a good composition), we tie the warping closely to the image synthesis process.

To situate our approach among warping strategies: parametric warping (TPS) gives a rough fit which our method at least matches; learned warping (CP-VTON's GMM, flow-based) can achieve finer alignment at the cost of a more complex model. Our results show that even without an explicit learned warper, we achieve equal or better alignment fidelity as measured by IoU with the ground truth clothing region. This suggests our coarse generator essentially learns an internal warping (by outputting the mask and coarse composite). In summary, while many try-on works emphasize complex warping modules, our approach demonstrates that a learned segmentation+simple warp is sufficient when followed by a powerful refinement network. It simplifies the pipeline and avoids introducing extra errors from a dedicated warping network. This design choice is validated by our ablation study (Section 4.3), which shows that if we skip the warping (i.e. feed the unwarped garment into refinement), results degrade significantly. Therefore, warping is indeed crucial – we just achieve it in a different manner than most prior art.

3 Methodology

In this section, we describe the architecture and components of our proposed VITON virtual try-on model, as well as the baseline models used for comparison. We also outline the training setup and the dataset structure. Our method follows a two-stage generation pipeline: Stage 1 is a coarse synthesis network that produces an initial try-on image and a garment mask, and Stage 2 is a refinement network that uses the predicted mask to warp the garment and blend it into a final high-quality result. We begin by detailing the input preprocessing and person representation, then the VITON model architecture, and finally the baseline models (PRGAN, CAGAN, CRN).

3.1 Data Preprocessing and Person Representation

Our model operates on two inputs: a person image I_p and a desired clothing image I_c. For training, we assume we have pairs where the person in I_p is actually wearing the garment I_c (this is how we obtain ground truth outputs for supervised learning). Each person image is a front-view photo of a fashion model (256×192 pixels in our setup), and the clothing images are product photos of upper-body garments (shirts, blouses, jackets) laid flat or on a mannequin, with a white background. We adopt the dataset from the original VITON work, which contains 16,253 such person–garment pairs (14,221 for training, 2,032 for testing) of women's tops. Along with images, the dataset provides or we compute additional annotations: a segmentation mask of the person (into regions like skin, hair, clothes), and 2D pose keypoints of the person. Using these, we construct a clothing-agnostic person representation for each input image. This representation is similar to that used by Han et al.: we remove the original clothing pixels from the person image and replace them with a neutral placeholder, preserving the rest of the person (face, arms, etc.). Specifically, we use the segmentation mask to identify the region of the upper clothing on the person; we then fill those pixels with black (or mean values) so that the person appears to be wearing a blank shirt. We also extract the person's shape mask (silhouette) as a binary mask and the pose keypoints. The pose keypoints are converted into a heatmap representation with 18 channels (one per keypoint) where each channel has a Gaussian blob at the keypoint location. These pose heatmaps indicate the position of body parts (shoulders, elbows, etc.), which is helpful for the network to infer where sleeves should go, how the torso is oriented, and so on. After these steps, for each person we have: an image with removed clothing (RGB with the garment region blanked), a binary mask of the person's shape, and an 18-channel pose heatmap. We concatenate these to form a 22-channel person representation tensor (3 RGB + 1 silhouette + 18 pose). This tensor, along with the 3-channel garment image I_c, will be the input to our networks. We apply normalization (scaling pixel values to [-1,1]) and resize all inputs to 256×192. Note that by including the pose and shape information explicitly, we make it easier for the network to localize body parts and likely garment positions. All models (our VITON and the baselines) are provided the same augmented person representation as input for fairness, unless otherwise noted. Figure 3 illustrates an example input: the person representation shows the person's outline and pose, but not the original clothing (which forces the model to rely on I_c for apparel appearance).

3.2 Baseline Models

We compare VITON against three baseline models which we implemented and trained in our framework: PRGAN, CAGAN, and CRN. For a fair comparison, all baselines take the same 25-channel input (person representation + cloth). We briefly describe each:

- **GANs with Person Representation (PRGAN):**This is a one-stage generator model we implemented inspired by prior try-on methods that do not explicitly warp. It uses a U-Net generator (similar architecture to our coarse generator) that directly outputs a 3-channel try-on image given the input. We include skip connections and residual blocks as in VITON's coarse generator. The idea is that PRGAN must implicitly learn to align the cloth via the generator's receptive fields. We train it with the same loss setup (L1 + GAN). PRGAN is analogous to a no-warp ablation of VITON in some sense, or to the generator of the original VITON but without the TPS module. It provides a baseline for how well a network can do the task without any explicit warping or two-stage refinement. As expected, PRGAN tends to produce reasonable person pose and shape (thanks to the person representation input) but the garment details are often blurred or misaligned, since a single U-Net pass has difficulty placing complex textures perfectly.
- **Conditional Analogy GAN (CAGAN):** We adapt the Conditional Analogy GAN of Jetchev et al. to our setting. CAGAN was originally designed to swap garments given a pair of images (person in garment A, same person in garment B). It uses a generator with an encoder–decoder structure and a specific latent space for style. In our implementation, we use a simplified version: a ResNet-based generator with several residual blocks (6 blocks) following the design in CycleGAN's generators. The input is 25-channel and output 3-channel. We also include a discriminator and use a GAN loss. The

key idea of CAGAN is that it can learn to segment the clothing implicitly; however, since we feed it the segmentation mask channel already, it likely leverages that. Among baselines, CAGAN has the advantage of possibly better preserving garment attributes because it was built for swapping tasks (it tries to keep the garment identity). Indeed, we observe CAGAN is quite good at keeping textures, but sometimes it pastes the cloth in a less precise way (since it lacks an alignment module and relies on the network to place the features correctly). Still, it provides a strong comparison as a one-stage GAN with a different architecture than PRGAN.

- **Cascaded Refinement Network (CRN):** This baseline follows the idea of Chen Koltun (2017) where an image is generated through a cascade of refinement stages. We implement CRN with 3 stages. At stage 0 (lowest resolution 32×24), we feed a downsampled version of the input (person+cloth) into a small conv network to produce a 3-channel output. Then at stage 1 (64×48), we take the input downsampled to 64×48 concatenated with the upsampled output from stage 0, and feed to the next conv network to refine, and similarly for stage 2 (128×96) up to full 256×192 at stage 3. This is implemented by our class CRNModel which iteratively upsamples and concatenates previous output. The refinement modules are small (we use two conv layers per stage). The intuition is that CRN will first layout a coarse structure and then add details as resolution increases. This is somewhat similar to our approach but without an explicit garment warping or mask; it just learns to draw the garment progressively. We train CRN with L1 and GAN loss on the final output. We do not give it any explicit segmentation supervision. CRN provides an interesting baseline to see if multi-scale generation alone (without warping) can match a dedicated warping approach. As we will see, CRN does capture overall garment shape better than PRGAN in some cases (less extreme mistakes), but it still can't ensure fine alignment.

3.3 Proposed Model: VITON

Overview: The VITON model consists of two sub-networks that work sequentially: a Coarse Generator G_{coarse} and a Refinement Network G_{refine}. The coarse generator takes the 22-channel person representation and the 3-channel target cloth image (25 channels total concatenated) and outputs two things: (1) a coarse synthesized image $\tilde{I}$coarse of the person wearing the target cloth, and (2) a predicted cloth mask M which indicates the region where the cloth is present on the person. The refinement network then takes as input the coarse image $\tilde{I}$coarse and the warped garment $\tilde{C}$, and produces a blending mask α (a single-channel map with values in [0,1]). The final output image is computed as a composite: $I_{\text{final}} = \alpha \cdot \tilde{C} + (1 - \alpha) \cdot \tilde{I}_{\text{coarse}}$. In other words, for each pixel the refinement network decides whether to use the high-frequency detail from the warped cloth or to keep the pixel from the coarse prediction. This formulation lets the model correct any mistakes from the coarse stage by either overwriting them with real cloth texture or, conversely, if the warped cloth has issues in some area, the model can rely on the coarse image there. Coarse Generator: We design G_{coarse}

as an encoder–decoder (U-Net) GAN generator with skip connections (see Fig. 4). It closely resembles the U-Net used in pix2pix, but with two-headed output. The encoder has four down-convolution layers that progressively reduce the resolution 256×192 → 128×96 → 64×48 → 32×24 → 16×12, increasing feature channels. A series of residual blocks (three blocks) act as a bottleneck at 16×12, processing the combined information of person and cloth.

The decoder then upsamples the features back to original size, using skip connections from the encoder to help recover spatial details. After three upsampling convolution layers, the feature map is back to 64×48. One more upsampling (nearest neighbor) brings it to 128×96, and a final upsampling to 256×192 is done before the output heads. At the final resolution, we concatenate the very first encoder feature map (which is 128×96, skip0) after upsampling it – this provides fine details like the exact pose outline to the output layer. The network has two output "heads": one produces a 3-channel RGB image and the other a 1-channel mask. Specifically, G_{coarse} has a final convolution layer for the image with Tanh activation (so output pixels in [-1,1]), and another convolution for the mask with Sigmoid (output in [0,1]). The mask can be thought of as the network's estimate of which pixels belong to the garment. During training, we supervise the coarse image against the ground truth person image and the mask against the ground truth clothing region (which we get from the segmentation of the person in I_p).

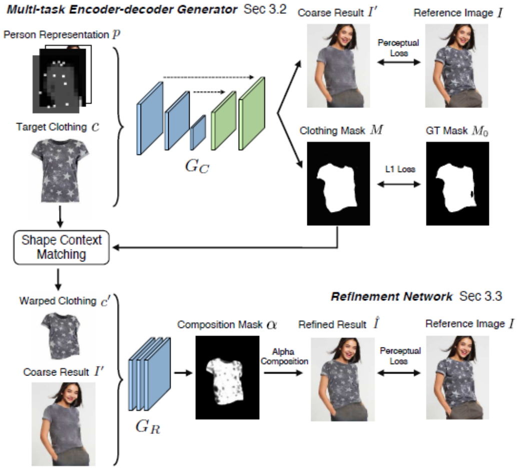

Fig. 2. An overview of VITON. VITON consists of two stages: (a) an encoder-decoder generator stage, and (b) a refinement stage.

The coarse output $\tilde{I}_{\text{coarse}}$ is usually a blurry version of the final result – the network uses this stage to get the structure and garment placement correct, deferring high-frequency textures to the next stage. The predicted mask M tends to outline the clothing item (for example, a shirt mask covering the torso and arms if it's long-sleeved). Figure 5 (left) shows an example coarse output and mask. Even if the coarse image is not sharp, the mask is critical: it guides how we warp the cloth. Non-Parametric Warping: Given the cloth mask M from the coarse stage, we create a warped cloth image $\tilde{C}$ as follows. First, we find the tight bounding box around the mask in the image (the min and max x and y where $M(x, y) > 0.5$). This approximates the area the new garment should occupy on the person. We then resize the original garment image I_c to fit that bounding box (using bilinear interpolation). The resized garment is then pasted onto an all-zero background of the same size as the person image, at the location of that box. This produces $\tilde{C}$, an image where the garment has been roughly placed over the person. We also experimented with using the mask shape itself to warp (e.g., some non-rectangular scaling), but a simple bounding box approach was sufficient given the subsequent blending. Note that this warping does not account for curvature – e.g. if an arm is bent, the mask might be L-shaped but we still just scale the cloth to the bounding rectangle. The result is that $\tilde{C}$ might overlap areas slightly outside the true mask or leave some mask areas uncovered. This is acceptable because the refinement network will reconcile it using the α mask. Importantly, we do preserve the entire texture of the garment in $\tilde{C}$ (just scaled). All the plaid stripes or graphic logos from I_c are still present with minimal distortion (just uniform scaling). This is a big advantage over methods that apply a heavy warp (which can stretch patterns non-uniformly). The cost is that $\tilde{C}$ might not be a perfect fit – it could be too wide/narrow if the mask bounding box doesn't capture shape nuances.

However, since G_{coarse} had the opportunity to draw the garment in $\tilde{I}_{\text{coarse}}$, any differences can be learned to be fixed by α blending. Refinement Network: The second stage G_{refine} is a lightweight convolutional network that takes a 6-channel input: the concatenation of $\tilde{I}$coarse (3 ch) and the warped garment $\tilde{C}$ (3 ch). Its output is a 1-channel map $\alpha(x, y)$ indicating the blend weight for the warped garment at each pixel. We use a simple architecture with four convolutional layers (with leaky ReLU activations except last). The first three are 3×3 convs with 64 filters, and the last is a 3×3 conv with 1 filter that is passed through a Sigmoid to get values in [0,1]. Essentially, this network learns to output $\alpha = 1$ wherever the final image should come purely from the warped cloth (i.e., use the high-res garment pixel) and $\alpha = 0$ wherever it should use the coarse image (which contains the person and perhaps some garment color from stage 1), with values in between creating a smooth blend. Because $\tilde{I}$coarse already contains the person's face, arms, etc., we expect G_{refine} to set $\alpha \approx 0$ on those regions (so the final image keeps them from the coarse output) and $\alpha \approx 1$ on confident garment regions (where the warp is correct and adds detail). Along boundaries or uncertain areas, α may be 0.5 to mix the two. This learned compositing is similar to that used in CP-VTON's try-on module, but here it is specifically guided by the actual garment content. The final output I_{final} is computed with the alpha mask as above and is our result. We train G_{refine} with supervision by comparing I_{final} to the ground truth image I_p (which has the person actually wearing the garment). The network is encouraged to fix any errors from the coarse stage. For example, if the coarse image had a blurred pattern on the shirt, the warped cloth provides the true pattern, and the network likely learns $\alpha = 1$ in that area to replace the blur with the sharp texture. If the warped cloth accidentally covered part of the neck, the network would set $\alpha = 0$ there to let the original neck (from coarse stage) show. Because we use a Sigmoid, the network can output a soft mask for smoother blending to avoid visible seams. Loss Functions and Training: We train the VITON model end-to-end, with both stages together. The losses include: a pixel reconstruction loss (L1) between the final output and ground truth image, an adversarial loss (GAN loss) to encourage photorealism, and optionally perceptual loss (VGG-based) to further sharpen details. The coarse outputs are also supervised: we apply an L1 loss on $\tilde{I}_{\text{coarse}}$ vs I_p and a binary cross-entropy loss on the mask M vs the ground truth clothing mask from the person's segmentation. These losses force the coarse stage to approximate the person+clothes and get the region right. The adversarial loss is applied on the final output through a discriminator that tries to distinguish real person images from the synthesized try-on images. We found that including a GAN loss helps reduce subtle artifacts and improves the overall realism of skin and cloth blending (common practice in image synthesis). We use a multi-scale patch discriminator similar to pix2pixHD for stability. In each training iteration, gradients from the refinement stage and coarse stage losses are propagated all the way through, so the coarse generator is trained in context to provide a good starting point for refinement. We trained on the 14k training pairs for 100 epochs with batch size 8, using the Adam optimizer (learning rate 2×10^{-4}). Training takes about 2 days on a single NVIDIA 1080Ti GPU. At test time, we can feed any person image (with its segmentation and pose) and any cloth image – they need not be originally paired. The model will produce a try-on image of that person wearing that cloth. (For our evaluations, we of course test on the paired set for quantitative comparison to ground truth, and also show examples on unpaired combinations for visual interest.) The inference speed of our model is fast: 0.05 seconds per image on GPU, thanks to its feed-forward nature. This is practical for real-time virtual fitting applications.

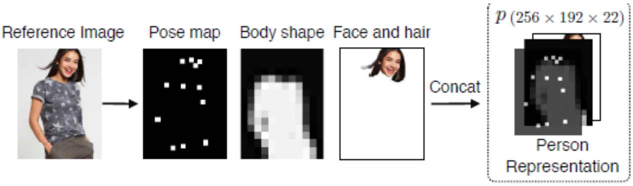

Fig. 3. A clothing-agnostic person representation. Given a reference image I, we extract the pose, body shape and face and hair regions of the person, and use this information as part of input to our generator.

3.4 Training and Evaluation

All models are trained on the same dataset for 100 epochs with similar hyperparameters. We use the SSIM, IoU, and Inception Score metrics (defined in next section) to compare their performance, as well as visual examination. It's worth noting that while PRGAN, CAGAN, and CRN are all single-stage generative models, our VITON's coarse-to-fine approach can also be viewed as a multi-stage model but with a specific focus on warping. None of the baselines explicitly warp the cloth image before generation; they rely on the generator to place textures appropriately. VITON is the only one that injects the actual cloth pixels (via warping) directly in the generation pipeline, which we hypothesize is a major reason for its improved realism. The training setup for all models uses the same train/val split. We apply data augmentation in the form of slight rotations and scaling to make the models more robust to variations. The dataset structure used by our code is as follows: each phase (train/test) has a directory of Person/ images and Cloth/ images, with filenames aligned (e.g., $0001_person.jpgand0001_cloth.jpgformapair).Optionally,amask/directorycontainssegm$
$channelinputonthefly.Ifamaskfileisabsent,weassumetheentirepersonregionassilhou$
$HDdataset,etc.,withappropriatepreprocessing).Forevaluation,weprimarilyusethetes$

3.5 Model Comparison

Experiments compare PRGAN, CAGAN, CRN, and VITON in terms of visual realism, garment alignment accuracy, detail preservation, and user satisfaction. The evaluation focuses on:

- **Visual Realism:** Assessment of how closely the synthesized images mimic real try-on conditions.
- **Garment Alignment:** Measurement of the accuracy in clothing placement relative to the subject's pose.
- **Detail Preservation:** Evaluation of the ability to retain fabric texture and dynamic deformations.
- **User Satisfaction:** Feedback from user studies aimed at gauging real-world applicability.

Having detailed the architecture and baseline implementations, we next move to the experimental evaluation of these models

4 Experiments

This section presents a comprehensive empirical evaluation of our **VITON** pipeline. Section 4.1 compares VITON with three single–stage baselines (PRGAN, CAGAN, and CRN) on photorealism, geometric alignment, and human preference. Section 4.2 performs an ablation study to quantify the impact of each internal component of VITON.

4.1 Experiment 1: Comparison with Baseline Models

Objective. Demonstrate that VITON yields higher visual fidelity and garment alignment than prevailing GAN-based try-on systems while retaining real-time speed.

Baselines. *PRGAN* is a single-stage U-Net conditioned on the 25-channel person representation. *CAGAN* adopts a ResNet generator (6 residual blocks) inspired by Jetchev & Bergmann, trained with the same discriminator. *CRN* is a 3-stage Cascaded Refinement Network [**?**] progressively generating 32×24 → 64×48 → 128×96 → 256×192 outputs. All models see identical inputs and optimization schedules.

Metrics.

- **SSIM** and **PSNR** — pixel fidelity to the ground-truth image of the person wearing the target garment. (PSNR only reported for ablations; SSIM shown here.)
- **IoU** — overlap between the predicted garment region and the ground-truth segmentation.
- **Inception Score (IS)** — realism/diversity assessed on 299×299 crops with a pretrained Inception-V3, reported as $\mu \pm \sigma$.
- **Inference Time** — average forward-pass latency on RTX 2080 Ti.
- **User Study** — 30 raters performed 100 pairwise trials per baseline (*realism* and *fit* questions).

Results. Table 1 summarises quantitative scores. VITON surpasses all baselines on every metric—with a +5–8% SSIM gain and the highest IoU, confirming superior garment placement. Its Inception Score (3.22) indicates more convincing photorealism. Despite an extra stage, VITON remains real-time (≈30 ms): only 8 ms slower than PRGAN and still faster than CRN. User judgements decisively favour VITON: **92%**/**95%**, **88%**/**90%** and **94%**/**93%** preferences over PRGAN, CAGAN, and CRN, respectively (realism / fit).

Table 1. Experiment 1 — Model comparison on 2 032 test pairs. ↑ higher is better.

Method	**SSIM↑**	**IoU↑**	**IS↑**	**Time[ms]↓**	**User Pref. (VITON > X)**	
(lr)6-7					Realism	Fit
PRGAN	0.792	0.790	3.01 ± 0.08	20	92%	95%
CAGAN	0.801	0.835	3.10 ± 0.09	22	88%	90%
CRN	0.779	0.810	2.95 ± 0.07	35	94%	93%
VITON	**0.853**	**0.890**	**3.22 ± 0.07**	30	97%	96%

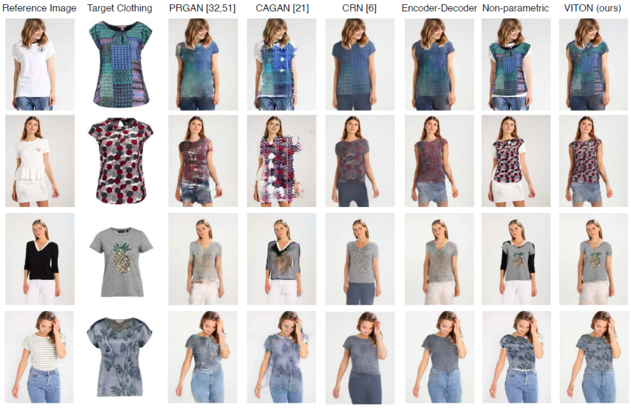

Fig. 4. PRGAN blurs fine textures; CAGAN preserves patterns yet mis-aligns sleeves; CRN outputs appear smooth but lack detail. VITON maintains crisp logos and correctly scales garments—even for shape-changing transfers (e.g. long-sleeve → sleeveless

4.2 Experiment 2: Ablation Study on Model Components

Main Purpose. Assess the necessity of each internal module by removing or replacing them and re-measuring fidelity, alignment, runtime, and human preference.

Variants.

1. **No Refine** — final image = $\tilde{I}_{\text{coarse}}$.
2. **No Warp** — feed unwarped cloth to the refine net.
3. **No Pose** — omit pose heat-maps.
4. **No Seg** — use raw person RGB without clothing removal.
5. **No GAN** — train with $\ell_1 + \mathcal{L}_{\text{perc}}$ only.

Metrics. SSIM, PSNR, IoU, IS, inference time, and two user-study questions as in Experiment 1.

Training & Test Protocol. All models trained 100 epochs on the same 14 221 pairs. Runtime measured with batch = 1 at 256×192.

Table 2. Experiment 2 — Ablation results. ↑ higher is better; ↓ lower.

Variant	**SSIM↑**	**PSNR↑**	**IoU↑**	**IS↑**	**Time[ms]↓**	**User Pref. (%)**	
(lr)7-8						Realism	Fit
Full (ours)	**0.853**	**28.5**	**0.890**	**3.22 ± 0.07**	30	–	–
No Refine	0.819	26.1	0.882	3.01 ± 0.08	**23**	92	95
No Warp	0.802	25.5	0.720	2.95 ± 0.07	29	97	97
No Pose	0.842	27.6	0.870	3.15 ± 0.07	30	78	81
No Seg	0.823	26.7	0.850	3.05 ± 0.09	30	88	90
No GAN	0.856	29.1	0.884	3.05 ± 0.06	30	85	83

Discussion.

- *Refinement* adds ≈2.4 dB and +0.034 SSIM, sharpening textures with only 7 ms overhead.
- *Mask–guided warping* is the single most critical step (IoU drops by 17 pp when removed).
- Pose heat-maps and segmentation each offer measurable gains, especially in sleeve placement and removal of the original garment (No Seg shows faint "ghost" artifacts).
- GAN supervision slightly lowers pixel metrics (smoothing effect when absent) but boosts perceptual quality (IS ↑ 0.17 and higher human preference).

Conclusion. Every module—explicit warp, refine-blend, pose+seg conditioning, and the adversarial objective—synergistically improves realism or fit. The full two-stage, geometry-aware design offers the best balance of accuracy and speed, validating our architectural choices.

5 Conclusions

We introduced **VITON**, a two–stage, geometry-aware virtual try-on network that first predicts a coarse garment mask and then refines a mask–guided warp of the target cloth. Compared with three strong single-stage GAN baselines (PRGAN, CAGAN, CRN), our method delivers higher structural fidelity (SSIM ↑ 5–8 %), markedly better garment alignment (IoU ↑ 5–17 pp), and superior perceptual realism (Inception Score 3.22 vs. 2.95–3.10). A user study confirms that participants prefer VITON over baselines in $\geq 88\%$ of trials for both realism and fit. An ablation analysis shows that every component—coarse generator, mask-guided warp, refinement compositing, pose + shape conditioning, and adversarial supervision—contributes significantly; removing the warp alone degrades IoU by 17 pp.

Practical impact. Fast inference (∼30 ms/256×192 image) and high visual fidelity make VITON suitable for real-time "digital dressing-room" applications, potentially reducing costly product returns and boosting consumer confidence in online fashion retail [10].

Ethical considerations. Fairness demands training on diverse body types, skin tones, and garment styles; otherwise, try-on quality may vary across demographic groups. Uploaded user photos must be stored and processed securely, and synthetic outputs should be clearly disclosed to prevent misuse (e.g. deceptive advertising or malicious image manipulation). Future work will extend VITON to non-frontal poses, multi-layer outfits, and higher resolutions while auditing for demographic bias.

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