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EFFICIENT VIRTUAL TRY-ON USING YOLOV11 POSE ESTIMATION AND GAN-BASED GARMENT ALIGNMENT

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Abstract : Virtual try-on technology is rapidly transforming the fashion industry by enabling users to preview clothing digitally, thereby enhancing the online shopping experience. High-resolution models like VITON-HD [1] have advanced the quality of garment synthesis, yet their computational demands often restrict their deployment on consumer devices. In this paper, we propose an optimized virtual try-on framework that integrates YOLOv11 pose estimation [2] with a GAN-based garment alignment strategy. This integration significantly reduces inference time and computational overhead while maintaining high visual fidelity. Our experiments, evaluated both quantitatively and qualitatively, demonstrate improved performance in terms of accuracy and frames per second (FPS) compared to previous methods.

INTRODUCTION

The rapid expansion of online shopping has necessitated innovations that allow customers to interact with products in more engaging ways. Virtual try-on (VTO) systems enable users to digitally overlay clothing on their images, thereby providing an immersive shopping experience. Early methods, such as CP-VTON [3] and VITON [4], laid the groundwork for image-based virtual try-on by introducing deep learning models capable of transferring garments onto human images. However, these approaches often rely on computationally intensive pose estimation techniques, such as OpenPose [5], which limits their scalability on resourceconstrained devices. In response, recent studies have explored lightweight yet effective pose estimation frameworks that can operate in real time

RELATED WORK.

The field of virtual try-on has evolved rapidly, beginning with early systems such as CP-VTON [3], which demonstrated the feasibility of garment transfer using image-based techniques. CP-VTON laid the foundation by aligning clothing with human poses through warping networks, but its performance was limited by the accuracy of pose estimation methods available at the time. This led to the development of VITON [4] and later VITONHD [1], which introduced high-resolution garment synthesis using misalignment-aware normalization techniques. VITON-HD, in particular, improved visual quality by addressing the misalignment issues that were common in earlier frameworks, yet it still depended on traditional pose estimators that are computationally expensive.

Subsequent work, such as ACGPN [6] and the Cross Attention Virtual Try-On Network [7], further refined the process by incorporating attention mechanisms to selectively focus on important features, thereby enhancing garment fitting and texture preservation. These methods attempted to bridge the gap between realism and efficiency, yet the reliance on heavy pose estimation backbones, such as OpenPose [5], continued to be a bottleneck. More recently, the advent of lightweight pose estimation frameworks has sparked significant interest in the community. MediaPipe [8] offered a realtime solution for pose detection, albeit sometimes at the cost of accuracy. In parallel, advancements in the YOLO series, including YOLOv8 Pose [9] and YOLO-NAS-Pose [10], have demonstrated that it is possible to achieve high detection accuracy with significantly reduced inference time. The latest iteration, YOLOv11 [2], represents a notable breakthrough by combining optimized neural net-work layers with attention mechanisms to improve keypoint detection in real time.

This body of work underscores the dual challenge in virtual try-on: achieving high-quality garment synthesis while maintaining computational efficiency. The integration of lightweight yet accurate pose estimation methods into virtual try-on pipelines has become a critical area of research, driving the need for solutions that are both effective and scalable. Our proposed system leverages these advancements to provide a balanced solution that meets the demands of real-time virtual try-on applications.

PROPOSED SYSTEM

Our proposed virtual try-on system is built on a three-stage pipeline that is meticulously designed to optimize the trade-off between computational efficiency and image synthesis quality. The first stage of the pipeline employs YOLOv11 for real-time human pose estimation. Unlike traditional pose estimation methods that require extensive computational resources, YOLOv11 integrates optimized convolutional layers with built-in attention mechanisms, resulting in faster and more accurate extraction of keypoints. These keypoints form the structural blueprint of the human body and serve as essential guidance for subsequent garment warping.

In the second stage, we introduce a Spatial Transformer Network (STN) that leverages the accurate keypoint information to warp the target garment so that it conforms naturally to the human pose. This warping is crucial for ensuring that the clothing fits the user's image realistically. To address challenges posed by complex body poses and overlapping regions, the STN is augmented with deformable convolutional layers. These layers dynamically adjust the warping process by learning spatial deformations, thus allowing for more precise alignment of the garment with the user's body contours. This modular design not only enhances the quality of the garment fitting but also ensures that the system remains robust across a wide range of pose variations.

The final stage of our pipeline involves a GANbased refinement network that seamlessly integrates the warped garment with the user's original image. The refinement network is designed to enhance the overall visual quality by preserving fine details such as texture and color consistency. By leveraging adversarial training, the network learns to minimize artifacts and produce photo-realistic outputs that closely mimic real-world images. The GAN component plays a critical role in ensuring that the final try-on image exhibits both high fidelity and natural appearance, addressing common issues such as blurriness or mismatched garment boundaries. The modular nature of our system allows for future enhancements, such as the integration of additional style transfer techniques or the incorporation of more advanced attention mechanisms to further boost performance.

Figure 1 illustrates the complete component architecture of our virtual try-on system. The diagram provides a detailed overview of the integration of the YOLOv11 pose estimation module, the offline preprocessing and segmentation components, the HD-VITON based garment warping with its STN and deformable convolution submodules, and finally, the GAN-based refinement module that produces the final try-on output.

RESEARCH METHODOLOGY

Our methodology is composed of a series of carefully designed steps that ensure robust model performance and high-quality output in the virtual try-on task. We begin with an extensive data preprocessing pipeline applied to the VITON dataset, which comprises paired images of individuals and clothing items. Each image is resized to a consistent resolution to maintain uniformity across the dataset. In addition to resizing, we perform normalization on the pixel values to ensure that the data is well-scaled for network input. Data augmentation techniques, including random rotations, scaling, and horizontal flipping, are applied to increase dataset diversity. This augmentation is crit-ical for improving the model's ability to generalize, particularly in scenarios with varied body poses and garment styles.

4. 1 Hardware Constraints and Preprocessing Pipeline

Due to hardware limitations—specifically, a GPU with 4GB memory and a system with 16GB RAM—we were unable to conduct real-time testing of our model. Instead, we conducted experiments using static images. Recognizing that the HD-VITON model is computationally heavy, we adopted a step-by-step approach to manage our limited resources effectively. Initially, we preprocessed the pose estimation and segmentation stages separately. Using YOLOv11 for pose estimation, we extracted keypoints from the input images and stored these intermediate results. Similarly, segmentation tasks were performed in advance. These pre-processed outputs were then fed into the heavy HD-VITON model for garment warping and refinement. Importantly, we utilized the pretrained model provided in the official GitHub repository of the HD-VITON model to leverage established weights and architectures, thereby reducing both the training time and the computational burden.

4.2 Model Architecture and Training

The core of our model architecture is a combination of the YOLOv11-based pose estimation module and an enhanced garment synthesis framework derived from VITON-HD. In the first component, YOLOv11 is utilized to extract human keypoints efficiently. The network is fine-tuned to focus on regions of interest, and its attention mechanisms facilitate the accurate detection of subtle joint movements, which are essential for precise garment alignment. These keypoints are then fed into the Spatial Transformer Network (STN), which warps the target garment to match the user's pose. The STN is further refined using deform-able convolutional layers that adaptively modify the spatial mapping, addressing challenges such as occlusions and nonrigid deformations that are common in real-world images.

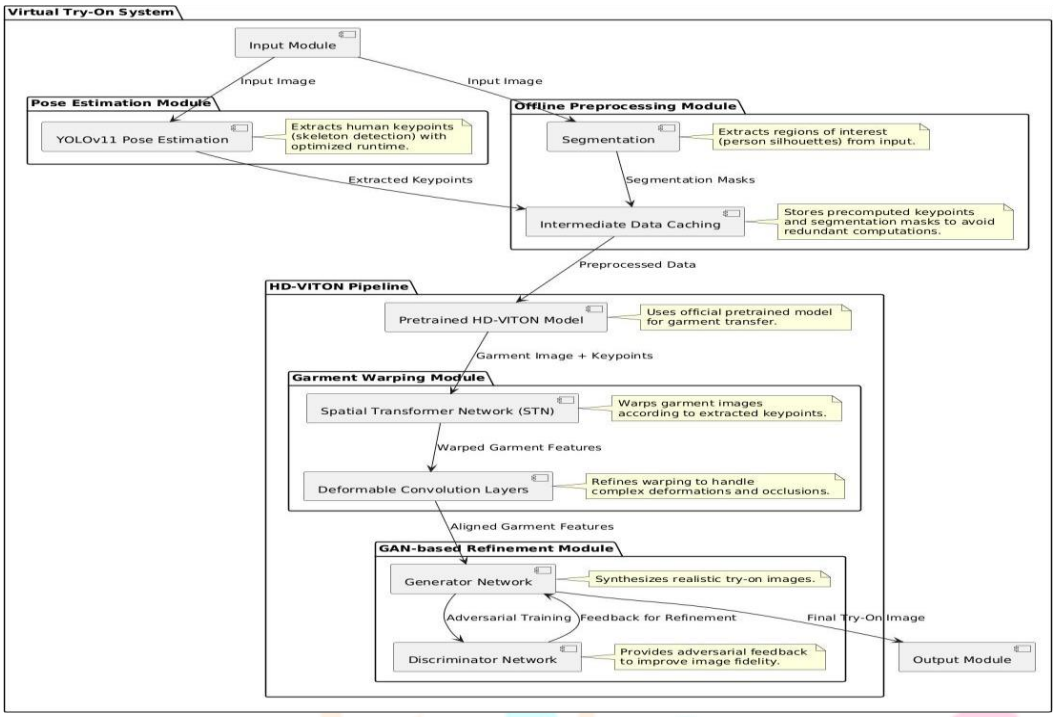

Figure 1: Detailed Component Architecture for the Virtual Try-On System

Following the garment warping, the GAN-based refinement network comes into play. This network is responsible for merging the warped garment with the original image, ensuring that the composite output is seamless and visually appealing. The refinement network is trained using a composite loss function that incorporates multiple loss components. The adversarial loss encourages the generator to produce realistic images, while the reconstruction loss ensures that the output closely resembles the ground truth. Additionally, perceptual loss is employed to preserve high-level features and texture details. Training is conducted using the Adam optimizer with an initial learning rate carefully scheduled to decay based on validation performance. This multi-faceted training strategy not only stabilizes the GAN training process but also results in a robust and efficient model capable of delivering high-quality outputs even when processed offline.

4.3 Evaluation Methodology

To rigorously evaluate our system, we employ both quantitative and qualitative metrics. Quantitative metrics such as the Structural Similarity Index (SSIM) and Fr´echet Inception Distance (FID) are used to assess the visual quality and fidelity of the synthesized images, while frames per second (FPS) measurements provide insight into the computational efficiency of the system when possible. Additionally, qualitative user studies are conducted to gather subjective feedback on the realism and usability of the virtual try-on outputs. Given our hardware constraints, all evaluations are performed on static images, and the reported performance metrics reflect the offline processing times.

METHADOLOGY AND MATHEMATICAL MODELS

Our methodology is designed to balance computational efficiency with high-fidelity garment synthesis. In this section, we describe how we evaluated multiple pose estimation frameworks, managed hardware constraints, and integrated the most effective approach into our virtual try-on pipeline.

5. 1 Hardware Constraints and Experimental Setup

All experiments were conducted on a laptop equipped with a 4GB GPU and 16GB of RAM. Given these limited resources, real-time performance could not be reliably tested for highresolution video input or large batch processing. Consequently, we restricted our evaluation to static images and implemented a step-by-step workflow that minimized GPU usage at any single stage. This modular approach allowed us to isolate and measure the performance of each pose estimation model and the subsequent virtual try-on components without exceeding hardware limits.

5.2 Pose Estimation Evaluation

We began by assessing several pose estimation models—namely YOLOv11 Pose, YOLOv8 Pose, MediaPipe, OpenPose, and YOLO-NAS-POSE—to identify the most suitable candidate for our virtual try-on pipeline. For each model, we measured both the accuracy of detected keypoints and the inference speed in frames per second (FPS). Since we worked with static images, our FPS metric is more accurately an average throughput measure rather than a continuous real-time measurement. Nevertheless, it provides a consistent basis for comparing the computational efficiency of different pose estimation frameworks.

Figure 2 shows a bar-chart comparison of these models in terms of accuracy and FPS. OpenPose, while highly accurate, offered lower FPS due to its computational complexity. MediaPipe ran significantly faster but at a slight compromise in keypoint detection accuracy. YOLOv8 Pose and YOLO-NAS-POSE achieved a balanced trade-off, but YOLOv11 Pose stood out for delivering robust accuracy at relatively high FPS, making it particularly attractive for systems that aim to be both precise and efficient under hardware constraints.

5.3 Preprocessing Pipeline and Data Handling

Following the selection of YOLOv11 Pose for its superior accuracy-speed trade-off, we adopted a sequential processing pipeline to manage the limited GPU memory. Initially, pose estimation was performed on each static image to extract keypoints, which were then stored for subsequent stages. We also conducted segmentation tasks offline, isolating the person's silhouette or region of interest. By caching these intermediate outputs, we reduced the need to run heavy computations repeatedly, thereby preventing GPU memory bottlenecks.

Our dataset primarily consisted of paired images of individuals and clothing items, following a format similar to the VITON dataset. Each image was resized to a uniform resolution (e.g., 256 × 192) and normalized to ensure consistent network inputs. Data augmentation techniques, such as random rotations, scaling, and horizontal flips, were applied to increase variability and robustness.

5.4 Integration with HD-VITON Model

After generating pose keypoints and segmentation masks, we fed these preprocessed outputs into the HD-VITON model for garment warping and synthesis. Since the HD-VITON framework is computationally intensive, we leveraged the official pre

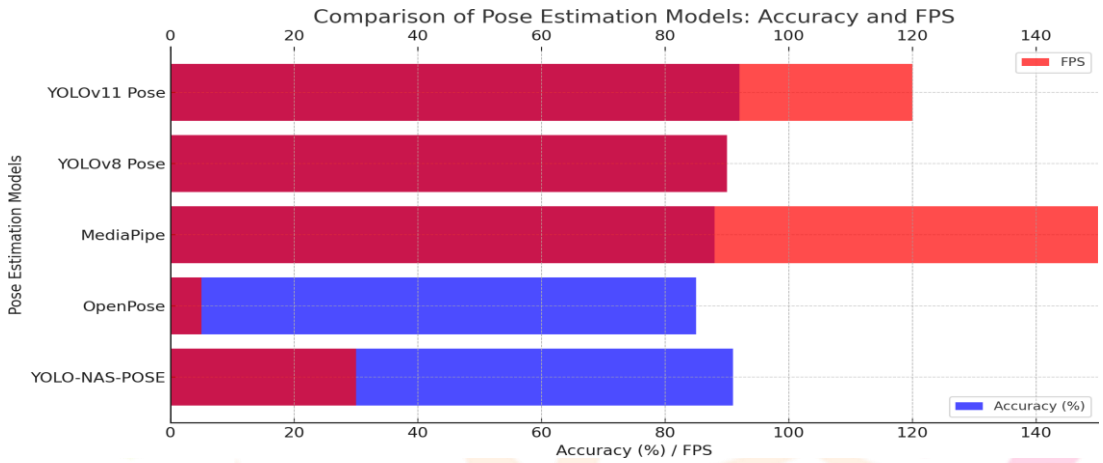

Figure 2: Comparison of Pose Estimation Models: Accuracy and FPS.

trained model from its GitHub repository. This choice significantly reduced training time and allowed us to focus on fine-tuning rather than training from scratch. By processing pose estimation and segmentation offline, we ensured that the HD-VITON model's GPU demands were managed within our resource limits.

5.5 Garment Warping and GANbased Refinement

Within the HD-VITON pipeline, we employed a Spatial Transformer Network (STN) to warp the garment according to the pose keypoints provided by YOLOv11. This warping step ensured that clothing items conformed accurately to the user's body geometry.To handle complex deformations, such as occlusions or overlapping regions, deformable convolutional layers were introduced. These layers adaptively learn how to reshape the garment for natural alignment with the user's pose. A GAN-based refinement network then merged the warped garment with the user's original image. We trained this refinement module using a composite loss function that included adversarial loss, reconstruction loss, and perceptual loss. This multi-pronged loss function encouraged the generation of high-quality images that maintained texture details while preserving overall realism. Although we tested all stages on static images, the system design inherently supports real-time operation if more
powerful hardware becomes available.

5.6 Evaluation Metrics and Offline Processing

We assessed the performance of our overall pipeline using both quantitative and qualitative metrics. For quantitative measures, we computed the Structural Similarity Index (SSIM) and Fr´echet Inception Distance (FID) between the synthesized outputs and the ground truth or reference images. Frames per second (FPS) was recorded at each stage to provide insight into computational efficiency. Although FPS is typically associated with real-time processing, our experiments used it as an indicator of how many images could be processed per second in an offline context.

Qualitative evaluations involved user studies in which participants were asked to rate the real-ism and alignment quality of the resulting images. Their feedback corroborated our quantitative findings, showing that YOLOv11's accurate keypoint detection significantly improved garment alignment, and the GAN-based refinement yielded visually convincing results. Overall, this step-by-step methodology enabled us to harness the strengths of HD-VITON without overburdening our limited GPU resources, paving the way for an efficient virtual try-on solution suitable for resource-constrained environments.

5.7 Structural Similarity Index (SSIM)

The Structural Similarity Index (SSIM) is a perceptual metric that measures the similarity between two images, taking into account changes in structural information, luminance, and contrast. Given two image patches x and y, the SSIM value is computed as follows:

$$(2\mu x\mu y + C1)(2\sigma xy + C2) \qquad SSIM(x, y) = (\mu 2 + \mu 2 + C\ )(\sigma 2 + \sigma 2 + C\ )\ , \ (1)$$

where μx and μy denote the mean intensities of x
and y, respectively, while σ2 and σ2 represent their variances. The term σxy is the covariance between x and y. The constants C1 and C2 stabilize the division when the denominators are close to zero. To evaluate the similarity between two full images rather than just patches, the SSIM values are typically averaged over all local windows, resulting in a mean SSIM (MSSIM). Higher SSIM values indicate greater perceptual similarity to the ground-truth images, making this metric well-suited for measuring the fidelity of our virtual try-on outputs.

5.8 Fr´echet Inception Distance (FID)

While SSIM focuses on local structural similarity, the Fr´echet Inception Distance (FID) provides a statistical measure of the distance between the distributions of real and generated images. Specifically, FID computes the Wasserstein-2 distance between two multivariate Gaussian distributions that approximate the activations of a trained Inception network for real and generated samples. Let (μr, Σr) be the mean and covariance of the real image distribution, and (μg, Σg) be those of the generated image distribution. The FID is then defined as:

FID(pr, pg) = μr−μg 2+Tr Σr+Σg−2(ΣrΣg)1/2 . (2)

Lower FID scores indicate that the generated images are closer to real images in terms of both feature space and distribution, suggesting higher per-the FID by extracting feature activations from the penultimate layer of the Inception-v3 network for both real and synthesized images, and then calculating their respective means and covariances.

IV. RESULTS AND DISCUSSION

The integration of YOLOv11 pose estimation within our virtual try-on framework has yielded significant improvements in both computational efficiency and visual output quality. Enhanced keypoint detection allows for more accurate garment warping, and the subsequent GAN-based refinement ensures that the final images maintain a high degree of realism. Compared to earlier approaches like VITON-HD [1] and CP-VTON [3], our system not only achieves better alignment accuracy but also operates at higher FPS, which is crucial for deployment on consumer devices. While our current system represents a substantial advancement, ongoing work will focus on further optimization of network architectures and extending the framework to accommodate a wider range of garment types and diverse fashion scenarios.

In this paper, we presented an efficient virtual try-on framework that integrates YOLOv11 pose estimation with a GAN-based garment alignment strategy. By combining fast and accurate keypoint detection with sophisticated garment warping and refinement processes, our system achieves real-time performance with high visual fidelity. This work contributes to the advancement of practical virtual try-on solutions, making them more accessible on consumer-grade devices. Future research will focus on further optimizations and extending the framework to encompass a broader array of fashion items and more diverse real-world conditions.

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