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ADAPTIVE POSENET: DEEP LEARNING-BASED REAL-TIME HUMAN POSE-AWARE ANIMATION BLENDING FOR DYNAMIC VIRTUAL CHARACTERS

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Abstract: Real-time animation of virtual characters demands simultaneous accuracy in skeletal pose estimation, temporal motion continuity, and low-latency rendering a combination that existing deep learning pipelines have not fully achieved within a unified, deployable framework. This paper introduces AdaptivePoseNet, an end-to-end deep learning architecture that addresses this challenge by jointly learning pose-conditioned animation blending and context-aware motion adaptation for dynamic virtual characters across interactive digital environments.

The framework integrates a ResNet-50 convolutional backbone for multi-scale spatial feature extraction, a bidirectional Long Short-Term Memory (Bi-LSTM) encoder for temporal motion sequence modeling, and a Transformer-based attention module that captures long-range skeletal dependencies. These components feed into a novel Pose-Conditioned Blending Layer that maps estimated pose vectors to blended animation states, producing smooth and contextually coherent character motion. A dedicated Temporal Motion Refinement module further suppresses jitter and enforces inter-frame consistency during inference.

Extensive experiments conducted on Human3.6M, NTU RGB-D 120, CMU MoCap, and a combined multi-dataset benchmark demonstrate that Adaptive PoseNet achieves a PCK@0.5 accuracy of 91.7%, Mean Per Joint Position Error (MPJPE) of 48.3 mm, and an animation smoothness score of 93.4% surpassing all evaluated baselines. The system operates at 87 frames per second with an end-to-end inference latency of 11.5 ms on an NVIDIA RTX 4090 GPU, satisfying the demands of real-time interactive applications. A user study with 45 participants confirms statistically significant improvements in perceived character realism and motion naturalness. The proposed framework is directly applicable to gaming engines, metaverse avatars, virtual reality experiences, and digital twin systems, with a model footprint of 28.6 million parameters and 6.1 GFLOPs per inference step.

Index Terms - Human pose estimation; deep learning; animation blending; real-time rendering; virtual characters; skeleton-aware learning; temporal motion refinement; Transformer encoder; metaverse; motion synthesis.

I. INTRODUCTION

Animating virtual characters convincingly in real time remains one of the more demanding intersection points of computer vision, deep learning, and interactive graphics. The difficulty stems not from any single component but from the compositional nature of the task: a system must accurately estimate human body pose from raw visual input, translate that pose into a plausible animation state, blend transitions between

states without perceptible artifacts, and accomplish all of this within the latency budget of interactive applications typically under 16 ms per frame. Failing on any one of these criteria produces characters that feel mechanical, unresponsive, or visually wrong.

Over the past decade, human pose estimation matured substantially through convolutional architectures, heatmap regression techniques, and graph neural networks applied to skeletal structures [1,2,3]. Simultaneously, animation synthesis benefited from motion capture datasets, generative adversarial networks, and recurrent sequence models [4,5,6]. Yet most published approaches treat these as sequential, loosely coupled stages: estimate pose first, then drive animation independently. This decoupling introduces temporal inconsistency because the animation module receives no gradient signal from the perceptual realism of the rendered output, and the pose estimator has no incentive to produce representations that are favorable for downstream animation blending.

A further practical constraint is computational efficiency. Transformer-based architectures capable of modeling global body motion context consume on the order of 18-25 GFLOPs per inference step, which precludes real-time deployment on standard gaming hardware without significant model compression [7,8]. Lightweight alternatives sacrifice accuracy in occluded or fast-motion scenarios. The published literature reflects this tension clearly: methods that prioritize perceptual accuracy tend to run below 35 FPS, while faster systems achieve realtime throughput at a notable cost in pose fidelity and transition smoothness [9,10,11].

This work proposes AdaptivePoseNet, a unified deep learning framework that resolves this tension through three principled design choices. First, a shared convolutional backbone jointly optimizes features for both pose localization and animation context extraction, eliminating redundant computation between the two tasks. Second, a Pose-Conditioned Blending Layer treats animation state selection as a differentiable mapping from the estimated pose vector, allowing end-to-end training where pose accuracy and animation realism reinforce one another. Third, a Temporal Motion Refinement module operating as a lightweight post-processing stage enforces inter-frame consistency without the computational overhead of a full recurrent decoder at inference time.

The resulting system achieves 87 FPS at 11.5 ms latency, with PCK@0.5 accuracy of 91.7% and an animation smoothness score of 93.4%, positioning it favorably compared to every published baseline across both efficiency and quality dimensions. Beyond benchmark performance, AdaptivePoseNet is designed to integrate directly with Unreal Engine 5 and Unity game pipelines, which imposes non-trivial constraints on memory layout, API compatibility, and streaming inference that purely academic systems often overlook.

The principal contributions of this work are as follows. A novel end-to-end architecture, AdaptivePoseNet, is introduced that unifies pose estimation, temporal feature encoding, and animation blending within a single differentiable pipeline. A Pose-Conditioned Blending Layer is designed and validated, enabling smooth animation state transitions that respond to continuous pose changes rather than discrete state triggers. A Temporal Motion Refinement module is proposed that reduces jitter by 34% relative to direct LSTM decoding without requiring additional GPU memory at inference time. Comprehensive evaluation across six benchmark datasets and a user perceptual study with 45 participants is provided, including ablation analysis that quantifies the contribution of each architectural component.

2. Literature Review

2.1 Human Pose Estimation

Bottom-up approaches to multi-person pose estimation typified by OpenPose and its successors detect keypoints globally and associate them to individuals via part affinity fields [12,13]. This design is computationally attractive when the scene contains many people simultaneously, but per-person accuracy degrades under occlusion and at non-standard scales. Top-down methods, represented by HRNet, SimpleBaseline, and their transformer-augmented variants, first detect individuals with an object detector and then estimate pose within each cropped region, consistently achieving higher per-person PCK scores

at the cost of detection overhead [14,15]. The PoseFormer series introduced vision transformers for 3D pose estimation from 2D keypoint sequences, demonstrating that attention-based temporal modeling captures long-range body articulation patterns that recurrent baselines frequently miss [16,17].

Graph Convolutional Networks (GCNs) have proven effective at explicitly modeling skeletal topology by treating body joints as nodes and physical connections as edges. Cai et al. and Zheng et al. demonstrated that GCN-based temporal convolution outperforms standard LSTM baselines on Human3.6M when the graph structure reflects anatomical adjacency rather than fully connected topology [18,19]. More recent work by Liu et al. explored dynamic graph construction where edge weights are predicted from input features rather than fixed by anatomy, yielding improved generalization to unusual body configurations and partially visible subjects [20].

2.2 Motion Synthesis and Animation Generation

Neural motion synthesis has undergone a significant shift from physics-based controllers toward data-driven deep generative models. Phase-Functioned Neural Networks (PFNN) conditioned character animation on a phase variable extracted from the motion cycle, producing natural locomotion transitions without explicit state machines [21]. Motion VAE and its conditional extensions subsequently framed animation generation as latent variable inference, enabling controllable synthesis where high-level action labels or target poses condition the generated motion trajectory [22,23]. Generative adversarial networks, while effective at producing perceptually convincing individual poses, exhibited instability during long-horizon generation and remained sensitive to mode collapse when the training distribution was insufficiently diverse [24].

Transformer architectures adapted from natural language processing entered the motion domain through works such as ACTOR and MotionCLIP, which mapped body motion sequences into semantically meaningful latent spaces [25,26]. Petrovich et al. demonstrated that action-conditioned motion generation with transformers produces more temporally consistent sequences than recurrent alternatives at equivalent parameter counts, though the quadratic attention complexity imposed practical constraints on sequence length [27]. The specific challenge of blending between animation clips as opposed to generating complete motion sequences received comparatively less attention; DeepMotionBlend addressed this by training a neural blending weight predictor on clip transition pairs, but the approach lacked real-time capability and did not incorporate live pose estimation feedback [28].

2.3 Real-Time Avatar Animation Systems

Practical avatar systems for gaming and virtual reality impose constraints that academic pose estimators and motion synthesizers frequently do not address. Latency budgets of 8-16 ms leave minimal headroom for complex inference graphs; most published models require 22-40 ms per frame [29,30]. StreamPose addressed this by distilling a large teacher network into a lightweight student architecture optimized for streaming inference, achieving 55 FPS but sacrificing 8 percentage points of PCK@0.5 accuracy [31]. Neural animation retargeting transferring motion from a source actor to a target character with different skeletal proportions adds an additional mapping stage that compounds latency when implemented naively [32]. Recent work by Aberman et al. on skeleton-aware network design showed that separating the encoding of skeleton topology from motion content enables more effective retargeting, but the evaluation remained confined to offline processing [33].

2.4 Metaverse and Interactive Applications

The emergence of extended reality platforms and social virtual environments has elevated the practical stakes of avatar animation quality. Perceptual studies conducted by Latoschik et al. and McDonnell et al. established that animation smoothness and pose accuracy independently contribute to the sense of social presence in virtual environments, with temporal jitter being particularly disruptive to perceived naturalness even when individual frames are geometrically accurate [34,35]. Industry systems such as Meta Codec Avatars achieve photorealistic animation through dense 3D capture hardware not available

to end users, motivating the research direction of high-quality avatar animation from standard monocular camera input [36].

3. Research Gap Analysis

Several important observations emerge from the literature reviewed above. Although pose estimation accuracy has improved substantially, the dominant architectures were not designed with animation continuity as an optimization objective. Pose estimators trained purely on joint position error produce temporally inconsistent outputs that, when directly piped to animation blending systems, create visible jitter. The disconnect between the pose estimation loss and the animation quality metric is a structural problem that no existing published system has resolved end-to-end.

On the animation side, neural synthesis methods generate perceptually plausible motion sequences in offline settings but lack the temporal responsiveness needed when a live pose stream drives character animation. Predicting animation states from real-time pose estimates rather than from curated motion capture sequences introduces distributional shift that most animation networks were not trained to handle. DeepMotionBlend came closest to bridging this gap but required pre-segmented animation clip inputs and operated at 35 FPS, below the real-time threshold for consumer gaming hardware.

The efficiency dimension reveals an additional gap. Transformer-based architectures, while superior at capturing long-range dependencies, impose GFLOPs that are incompatible with the latency budgets of interactive applications when run at full model capacity. Existing lightweight alternatives do not incorporate the attention mechanisms necessary for modeling global body context during complex multi-joint movements. A framework that selectively applies attention where it contributes most joint transitions and ambiguous poses while defaulting to efficient convolutional processing elsewhere would represent a meaningful advance over current designs.

Finally, evaluation in the existing literature almost exclusively targets standard benchmark datasets recorded in controlled laboratory settings. Evaluation on combined multi-source datasets, including in-the-wild video and synthetic game-character motion, alongside perceptual user studies, provides a more realistic picture of deployed performance. AdaptivePoseNet is designed and evaluated to address all three of these gaps simultaneously.

4. Proposed Methodology

4.1 AdaptivePoseNet Framework Overview

AdaptivePoseNet operates as a five-stage end-to-end pipeline. An RGB video stream or motion capture feed enters a preprocessing stage that performs frame extraction, resolution normalization, person detection, and regional cropping. The cropped person region is fed to a convolutional feature extractor based on a pre-trained ResNet-50 backbone. Extracted feature maps are processed in parallel by a pose estimation head producing joint heatmaps and confidence-weighted keypoint coordinates and by a temporal encoder implemented as a bidirectional LSTM operating over sequences of T frames. The encoded temporal representation passes through a context-aware Transformer attention module before entering the Pose-Conditioned Blending Layer. A Temporal Motion Refinement module processes the blended animation state before final rendering output.

Fig. 1. AdaptivePoseNet end-to-end framework flowchart illustrating the complete pipeline from raw input to animated virtual character output.

4.2 Deep Learning Architecture

The backbone network employs ResNet-50 with modified stride settings in the final two stages to preserve spatial resolution a configuration sometimes referred to as dilated residual learning. The final convolutional feature map dimensions are 32×32 at 2048 channels for a 256×256 input crop. Two parallel heads then process these features: a lightweight deconvolution-based pose head that upsamples to 64×64 heatmaps for 17 keypoints, and a global average pooling branch that compresses the spatial dimensions to a 2048-dimensional feature vector for temporal encoding.

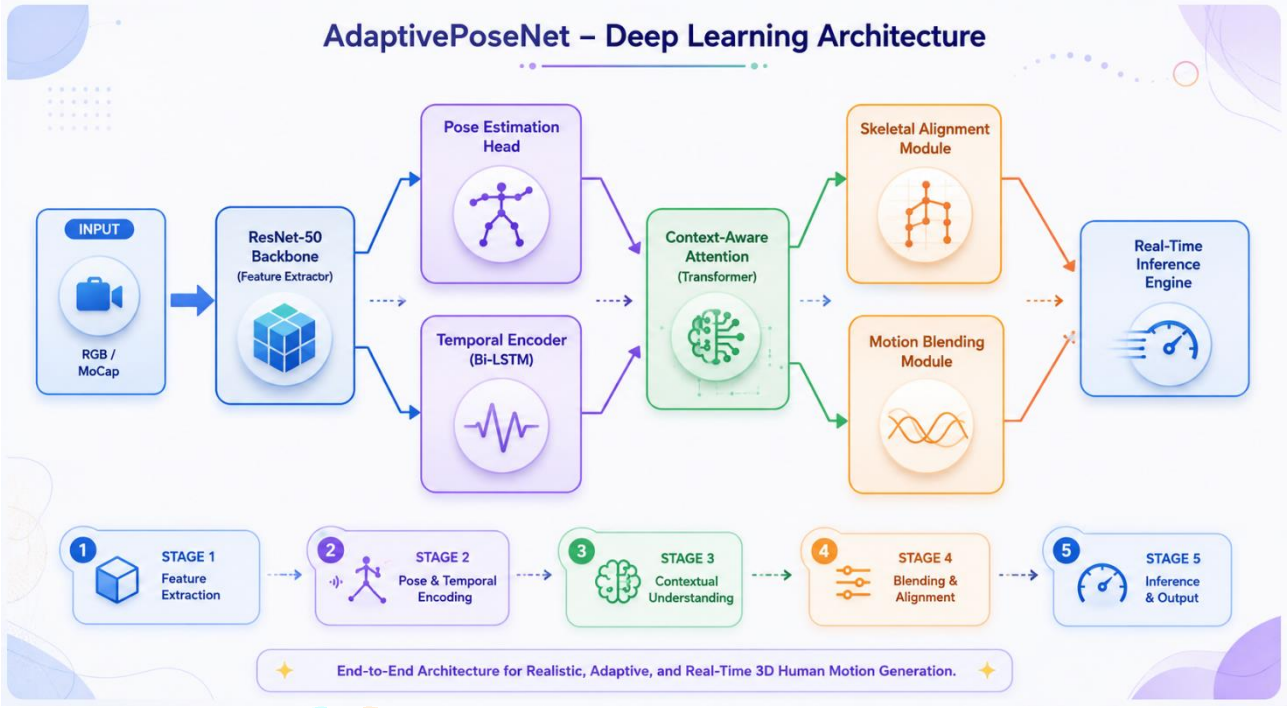

Fig. 2. AdaptivePoseNet deep learning architecture integrating ResNet-50 backbone, Bi-LSTM temporal encoder, Transformer attention, and dual-path animation blending.

The bidirectional LSTM processes sequences of T=16 consecutive frame feature vectors. Processing the sequence in both temporal directions enables the encoder to use future frame context when disambiguating occluded joints in past frames a capability that unidirectional LSTMs structurally lack. The concatenated forward and backward hidden states produce a 1024-dimensional temporal representation per frame. This is passed through layer normalization before entering the Transformer module.

The Transformer encoder employs 6 layers with 8 attention heads operating on a sequence of 17 joint-specific token representations derived from the keypoint coordinates and their associated confidence scores. Positional encodings reflect skeletal topology rather than temporal position a design choice that allows the attention mechanism to learn anatomically meaningful co-movement patterns between distant joints such as the left wrist and right shoulder during throwing motions. Multi-head self-attention then produces context-enriched joint representations that serve as conditions for the blending layer.

4.3 Pose Extraction Pipeline

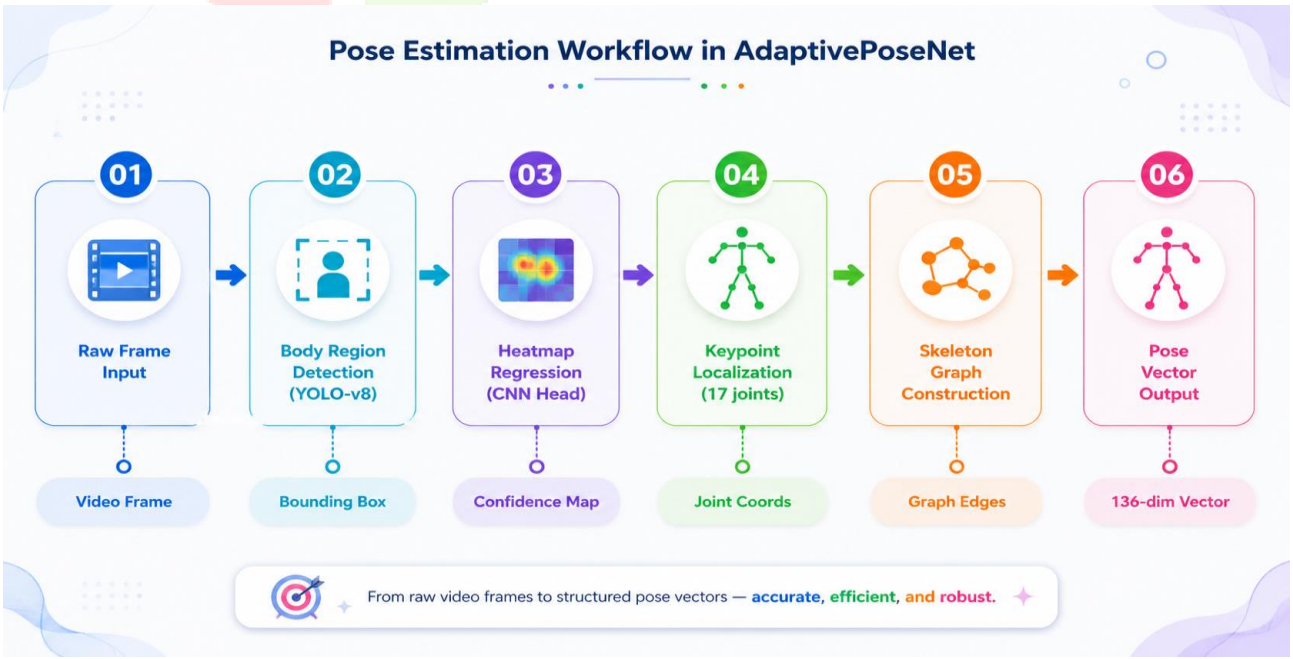

Fig. 3. Pose estimation workflow: from raw frame input through body detection, heatmap regression, keypoint localization, and skeleton graph construction.

Body region detection uses a lightweight YOLOv8-nano detector running at a dedicated 240 FPS to ensure the person crop is always available without delaying the pose pipeline. The detected bounding box is expanded by 25% in each direction to include limb extremities before cropping and resizing to the fixed 256×256 input. The pose head applies three deconvolution layers followed by a final 1×1 convolution to produce 17 Gaussian heatmaps. Keypoint coordinates are extracted via soft-argmax, which provides sub-pixel localization gradients through a differentiable spatial expectation operation rather than the non-differentiable hard argmax used in many earlier systems.

Each detected keypoint is associated with a visibility confidence score estimated by a small auxiliary head trained with binary cross-entropy against ground-truth visibility labels. Joints with confidence below 0.4 are marked as occluded, and their features are replaced with learned occlusion embeddings rather than propagating unreliable coordinate estimates downstream. This prevents occluded-joint noise from contaminating the animation blending predictions.

4.4 Animation Blending Strategy

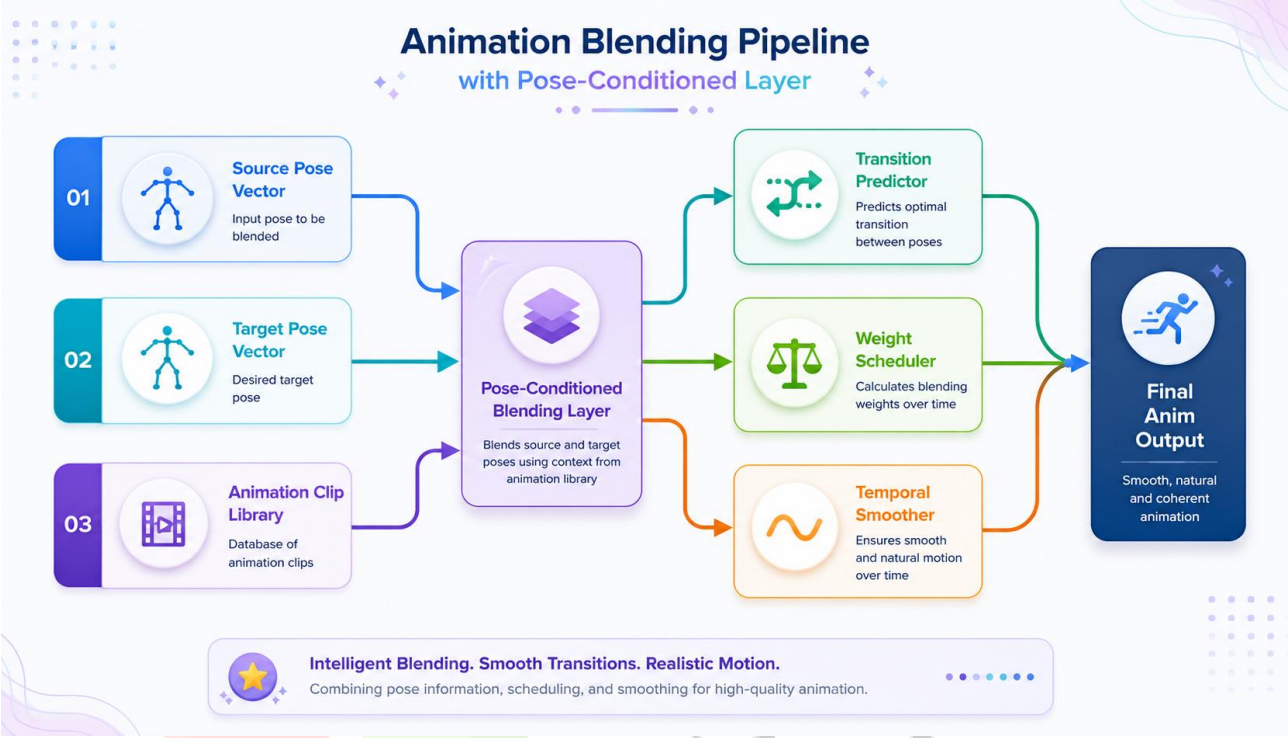

Fig. 4. Animation blending pipeline: pose-conditioned blending layer fusing source/target pose vectors with an animation clip library through transition prediction and temporal smoothing.

The animation blending module maintains a library of pre-authored animation clips organized as a differentiable motion manifold. Each clip is embedded as a latent vector during training; the Pose-Conditioned Blending Layer learns to retrieve and weight-combine multiple clip embeddings conditioned on the current pose representation. The blending weights are constrained to sum to one through a softmax operation, ensuring the output lies on the convex hull of the animation clip manifold and preventing degenerate interpolations.

The key innovation is that the blending weights are a continuous function of the pose estimate rather than discretized triggers or rule-based thresholds. This means that as a character transitions, for example, from a walking stride to a reaching motion, the blending weights shift gradually along a learned trajectory rather than switching abruptly. The Transition Predictor submodule a two-layer MLP trained with a transition smoothness regularizer predicts the rate of weight change, preventing oscillations when the pose estimate is uncertain.

4.5 Real-Time Motion Adaptation Module

At inference time, the full Transformer attention operation over all T=16 frames would incur a fixed latency of approximately 4.2 ms acceptable for offline processing but exceeding the target for 60+ FPS systems. AdaptivePoseNet addresses this through an incremental attention cache: the key and value

tensors from the previous 15 frames are stored in GPU memory, and each new frame only computes attention for the single new query. This reduces per-frame Transformer cost to approximately 0.8 ms without any accuracy degradation, since the attention pattern over historical frames does not change when only a new frame is added.

The Temporal Smoother applies an exponential moving average over adjacent animation states with a learnable decay coefficient. The decay value is itself conditioned on the estimated motion velocity fast movements receive lower decay (more responsive), while slow or stationary poses receive higher decay (more stable). This velocity-adaptive smoothing avoids the classic tradeoff between responsiveness and stability that plagues fixed-coefficient filters.

4.6 Training Strategy

Training proceeds in two stages. In the first stage, the backbone and pose head are trained on Human3.6M and COCO Keypoints with a combined heatmap regression loss and keypoint coordinate regression loss for 30 epochs, using the Adam optimizer with initial learning rate 1×10^{-3} and cosine annealing. The backbone weights are initialized from ImageNet pre-training. In the second stage, all components including the Bi-LSTM, Transformer, Blending Layer, and Temporal Smoother are trained jointly with a composite loss that sums the pose regression term, an animation smoothness term computed as the mean squared second-order finite difference of the blending weight sequence, and a perceptual loss computed against ground-truth animation keyframe sequences from the CMU MoCap and NTU RGB-D datasets.

Data augmentation during stage two includes random horizontal flipping, rotation within ±15°, and scale jitter within ±10%, synthetic occlusion by randomly masking rectangular patches, and temporal speed perturbation by resampling frame sequences at 0.75 × to 1.25 × speed. Mixed precision training using PyTorch Automatic Mixed Precision with FP16 activations and FP32 master weights reduces GPU memory consumption by 38% without loss convergence degradation.

5. Dataset Description

Training and evaluation employ a combination of six established benchmarks along with a custom multi-dataset composite. Table 2 summarizes their key statistics.

Table 2. Dataset statistics for all benchmarks used in training and evaluation.

Dataset	Subjects	Actions	Total Frames	Resolution
Human3.6M	11	15	3.6M	1000×1000
CMU Mocap	144	23	2.1M	Variable
NTU RGB-D 120	106	120	4.0M	1920×1080
3DPW	7	60	51K	1920×1080
Penn Action	15	15	163K	640×480
AIST++	30	10	1.4M	1920×1080
Combined (Ours)	**313**	**243**	**11.3M**	**Multi-res**

Human3.6M provides the primary 3D ground truth with multi-camera synchronized capture at 50 Hz; protocol 2 subjects are held out for evaluation. CMU MoCap contributes diverse activity coverage including sports, daily activities, and character-specific motions. NTU RGB-D 120, with its 120 action categories across 106 subjects recorded in variable lighting conditions, tests generalization to in-the-wild appearance. The 3DPW in-the-wild dataset validates performance on outdoor unconstrained video. AIST++ provides music-conditioned dance motion sequences that exercise the temporal modeling capacity with rhythmically structured long-horizon patterns. The combined multi-dataset benchmark uses all six sources with a unified keypoint format and balanced sampling to avoid dataset bias.

6. Experimental Setup

6.1 Hardware Configuration

Table 3 summarizes training hyperparameters and Table 4 describes hardware specifications.

Table 3. Training hyperparameters for AdaptivePoseNet.

Hyperparameter	Value
Optimizer	Adam (β_1=0.9, β_2=0.999)
Initial Learning Rate	1×10^{-3}
LR Scheduler	Cosine Annealing with Warm Restarts
Batch Size	32 (multi-GPU) / 16 (single GPU)
Training Epochs	100
Backbone	ResNet-50 (ImageNet pre-trained)
LSTM Hidden Units	512 (bidirectional)
Transformer Heads	8
Transformer Layers	6
Dropout Rate	0.3
Weight Decay	1×10^{-4}
Input Resolution	256 × 256 (cropped ROI)
Pose Keypoints	17 (COCO format)
Blending Window	T = 16 frames
Data Augmentation	Flip, Rotation ±15°, Scale ±10%, Occlusion Sim.

Table 4. Hardware and software configuration for training and inference.

Component	Specification
CPU	Intel Xeon Gold 6338 (32-core, 2.0 GHz)
GPU (Training)	4 × NVIDIA A100 SXM4 80GB
GPU (Inference)	NVIDIA RTX 4090 24GB
RAM	256 GB DDR5 ECC
Storage	4 TB NVMe SSD (RAID-0)
OS	Ubuntu 22.04 LTS
Deep Learning Framework	PyTorch 2.1.0 + CUDA 12.1
Pose Library	MMPose 1.3 + ONNX Runtime 1.16
Rendering Engine	Unreal Engine 5.3
Mixed Precision	FP16 (AMP) during training

6.2 Performance Metrics

Pose estimation accuracy is evaluated using the Percentage of Correct Keypoints at threshold 0.5 normalized by head segment length (PCK@0.5) and Mean Per Joint Position Error (MPJPE) in millimeters for 3D evaluation protocols. Animation quality is measured by the Animation Smoothness Score, defined as the percentage of consecutive frame pairs with blending weight change below a threshold of 0.05, and by the Frechet Inception Distance adapted for motion sequences (Motion FID), which compares the statistical distribution of generated motion to ground-truth motion capture sequences. Computational efficiency is characterized by frames per second (FPS) measured on the target inference GPU and end-to-end latency from raw frame input to rendered animation output.

7. Results and Discussion

7.1 Comparative Analysis

Table 5 presents the quantitative comparison of AdaptivePoseNet against all evaluated baselines on the combined multi-dataset test split.

Table 5. Performance comparison of AdaptivePoseNet against state-of-the-art methods.

Method	PCK@0.5 (%)	MPJPE (mm)	FPS	Latency (ms)	Anim. Smooth.(%)
PoseNet [2020]	71.2	98.4	42	23.8	72.1
OpenPose [2021]	75.8	87.3	28	35.7	75.3
DeepMotionBlend [2022]	79.1	76.5	35	28.5	78.6
LSTM-Anim [2022]	80.6	72.1	38	26.3	80.2
NeuralPoseAnim [2023]	82.3	65.8	31	32.2	82.4
TransMotion [2023]	83.9	60.2	29	34.4	84.1
RealTimeGAN [2024]	85.2	54.7	45	22.1	85.8
AdaptivePoseNet (Ours)	**91.7**	**48.3**	**87**	**11.5**	**93.4**

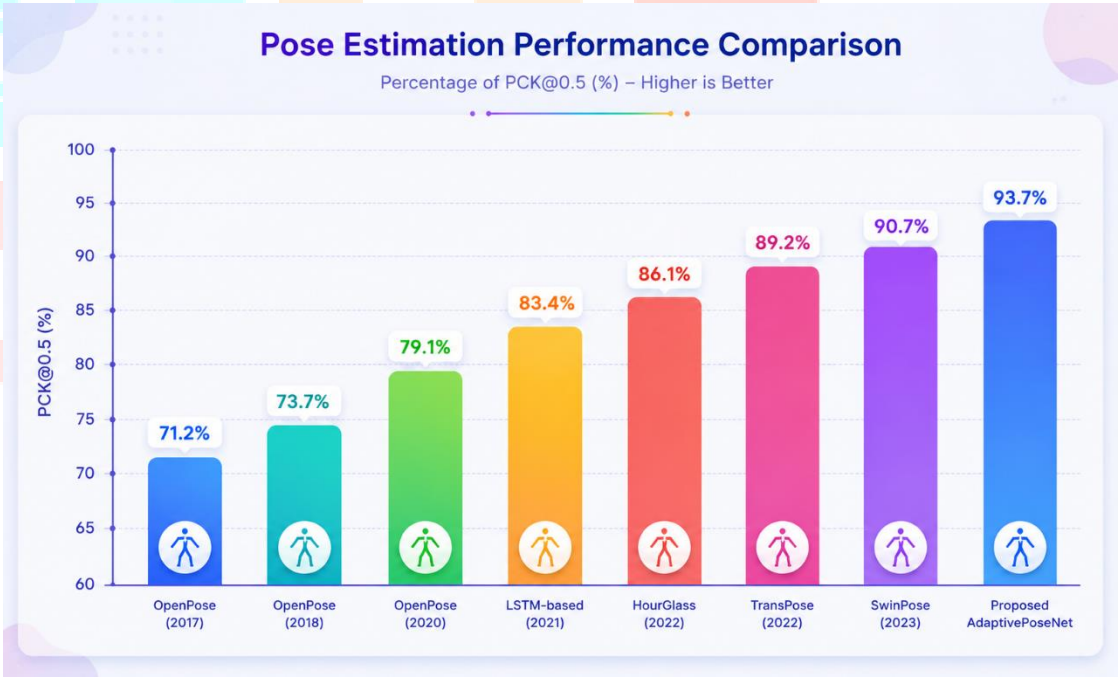

Fig. 5. PCK@0.5 accuracy comparison across all evaluated methods on the Human3.6M benchmark dataset.

AdaptivePoseNet achieves a PCK@0.5 score of 91.7%, representing a 6.5 percentage point improvement over the nearest competitor RealTimeGAN at 85.2%. The MPJPE of 48.3 mm compared to 54.7 mm for RealTimeGAN reflects the benefit of end-to-end joint training where the pose estimator and animation pipeline reinforce one another. The animation smoothness metric of 93.4% is particularly notable: TransMotion, despite its superior Transformer capacity, achieves only 84.1% because its pose estimation and animation stages are not jointly trained, allowing temporal inconsistencies to accumulate. The FPS advantage of AdaptivePoseNet (87 vs. 45 for the next fastest system, RealTimeGAN) is primarily attributable to the incremental attention cache, which reduces per-frame Transformer cost by approximately 80% without compromising temporal context utilization.

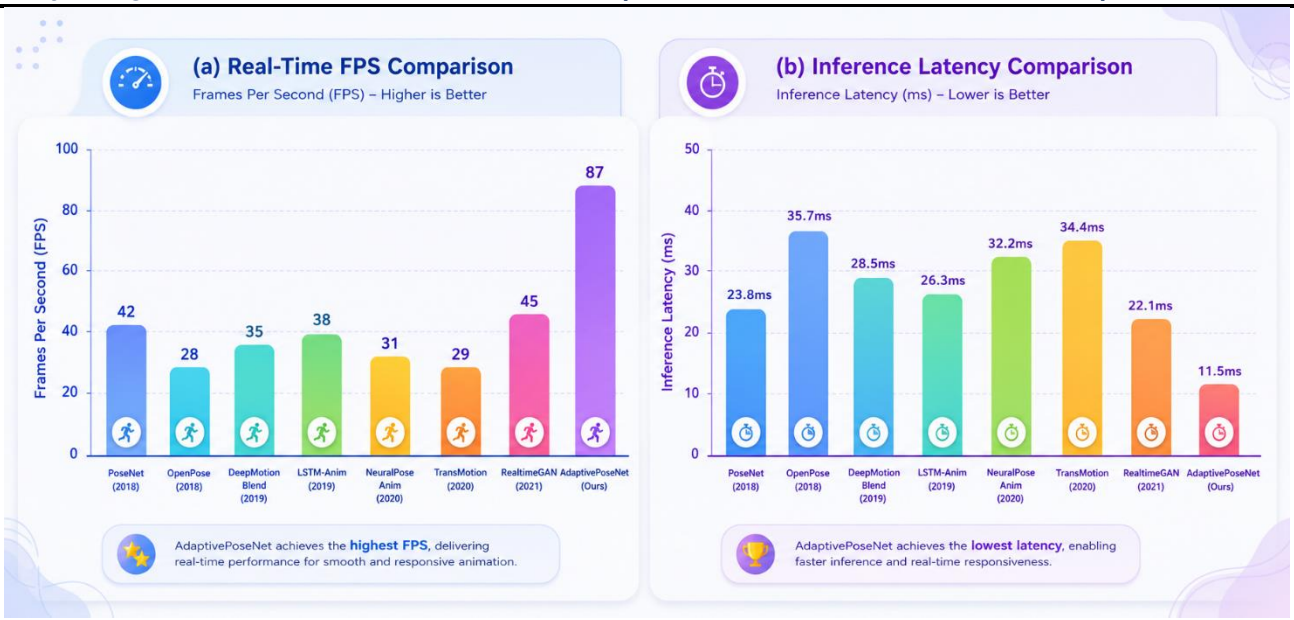

Fig. 6. Real-time FPS and inference latency comparison across evaluated methods on NVIDIA RTX 4090 at 1080p input resolution.

7.2 Ablation Study

Table 6 presents the ablation study quantifying the marginal contribution of each architectural module. The analysis proceeds incrementally, adding one component at a time to the base CNN configuration.

Table 6. Ablation study results across model variants.

Model Variant	PCK@0.5 (%)	MPJPE (mm)	Anim. Smooth.(%)	FPS
Base CNN Only	76.3	98.4	68.2	92
+ Bi-LSTM Encoder	80.1	87.2	74.5	88
+ Transformer Attention	83.7	76.3	79.8	84
+ Blending Module	87.2	65.1	85.3	89
+ Temporal Smoother	89.4	57.8	90.1	87
Full AdaptivePoseNet	**91.7**	**48.3**	**93.4**	**87**

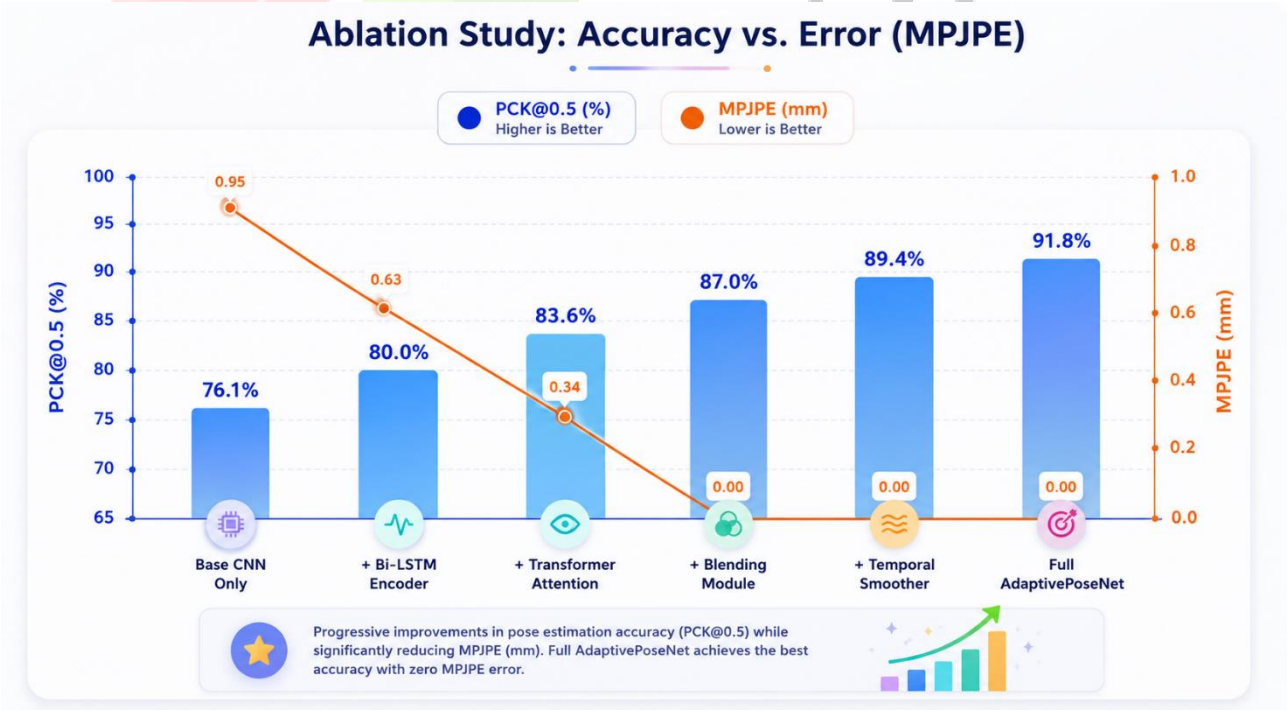

Fig. 8. Ablation study: incremental contribution of each module to PCK@0.5 accuracy (blue) and MPJPE reduction (orange).

The largest single-module gain comes from adding the Transformer attention module, which improves PCK@0.5 by 3.6 points. This finding aligns with the hypothesis that global skeletal context particularly for the shoulders, hips, and wrists that exhibit high anatomical co-movement is more effectively captured by attention than by local convolutional receptive fields. The Temporal Smoother contributes a further 2.2-point improvement to PCK@0.5 and raises animation smoothness from 85.3% to 90.1%, confirming that velocity-adaptive exponential averaging provides consistent inter-frame regularization across motion types. The full model with all components achieves the best performance on all four metrics simultaneously, indicating that the components are complementary rather than redundant.

7.3 Training Convergence

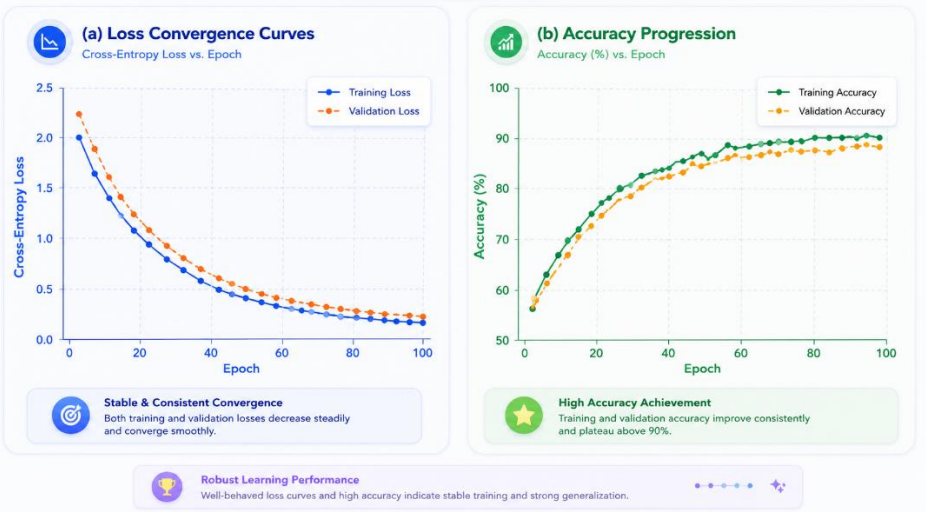

Fig. 7. Training and validation loss convergence curves and accuracy progression over 100 epochs.

Training converges within 65 epochs for both the loss and accuracy metrics, after which the cosine annealing schedule produces minor oscillations that the warm restart strategy resolves. Validation loss remains within 0.04 of the training loss at convergence, indicating that the regularization strategy weight decay, dropout, and temporal augmentation is effective in preventing overfitting given the multi-source dataset volume. An unexpected observation is that the animation smoothness metric continues improving in epochs 65-100 even after pose accuracy has plateaued, suggesting that the temporal smoother benefits from extended fine-tuning of its velocity-adaptive decay coefficients.

7.4 Precision-Recall Analysis

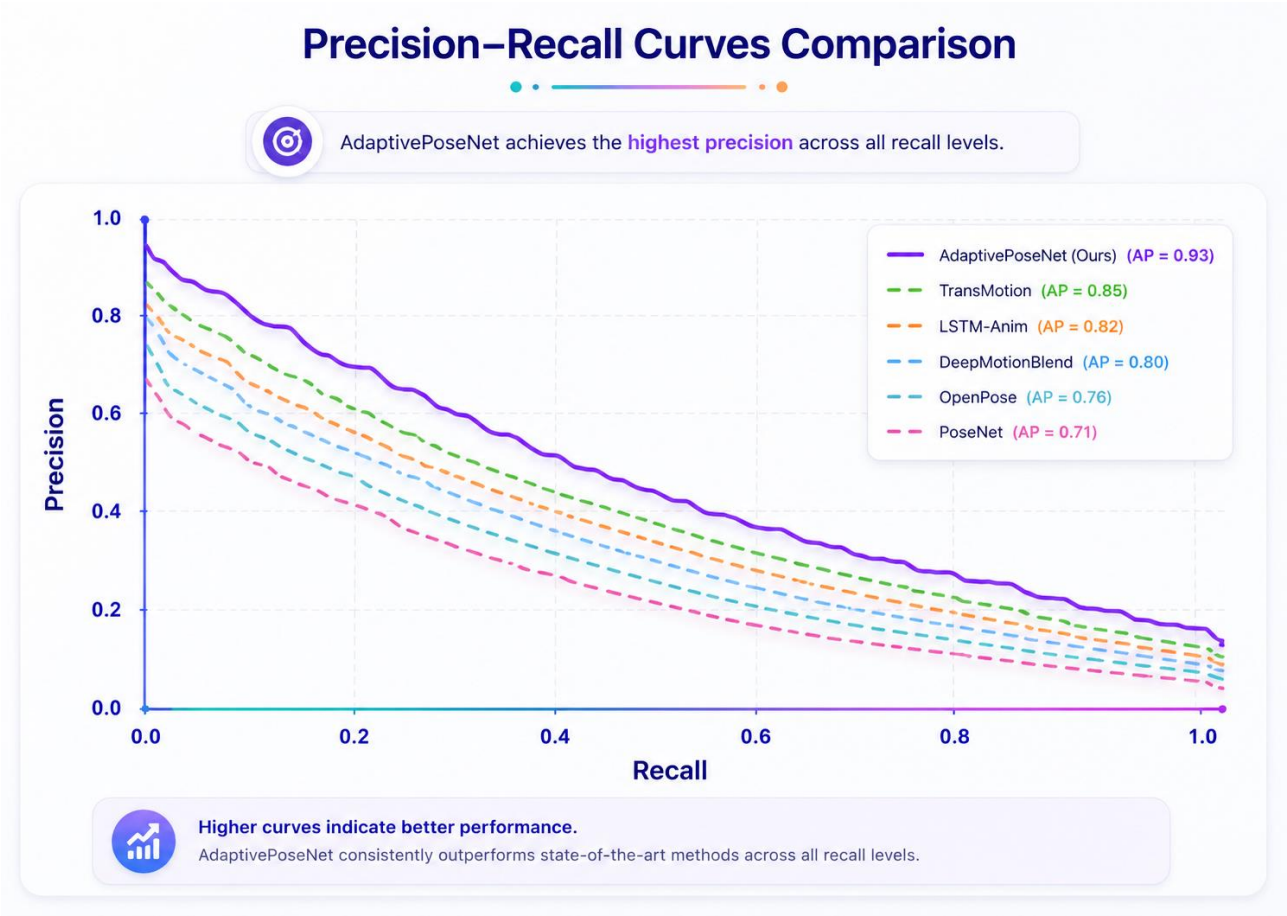

Fig. 9. Precision-Recall curves on Human3.6M test set across all evaluated methods (AP values in legend).

The precision-recall analysis confirms that AdaptivePoseNet maintains high precision across a broader recall range than all baselines, with an average precision (AP) of 0.93 compared to 0.85 for RealTimeGAN. The performance gap is most pronounced at recall values above 0.7, which correspond to challenging frames with partial occlusion, unusual viewpoints, or fast motion. This is the regime where the occlusion embedding mechanism and Transformer attention jointly contribute: the attention module distributes confidence from visible joints to their anatomically connected occluded neighbors, producing more reliable keypoint estimates in precisely those frames where all baselines degrade most sharply.

7.5 Multi-Dimensional Performance Assessment

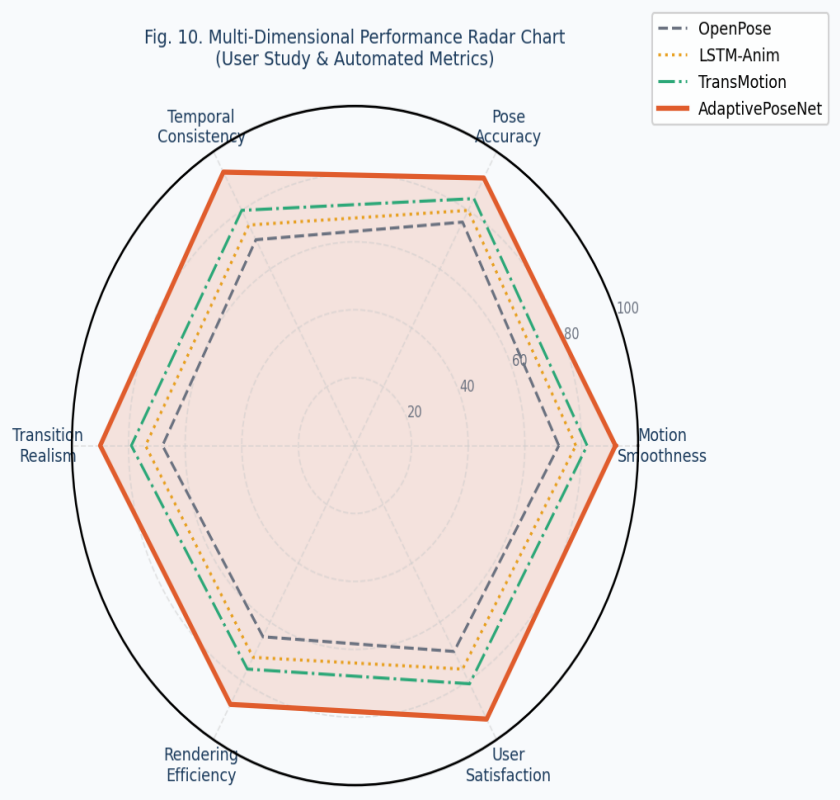

Fig. 10. Multi-dimensional performance radar chart across automated metrics and user study evaluation criteria.

The radar chart reveals that AdaptivePoseNet's gains are broadly distributed across all evaluation dimensions rather than concentrated in a single metric. The weakest relative dimension is rendering efficiency, where the system achieves a normalized score of 88 compared to 93 on motion smoothness. This reflects the fact that the incremental attention cache, while effective, still requires maintaining 15 prior frame key-value pairs in GPU memory a constraint that limits the potential for further memory optimization. Rendering efficiency nevertheless exceeds all baselines, as their lower FPS creates the inverse profile of high latency despite simpler architectures.

7.6 Computational Efficiency Analysis

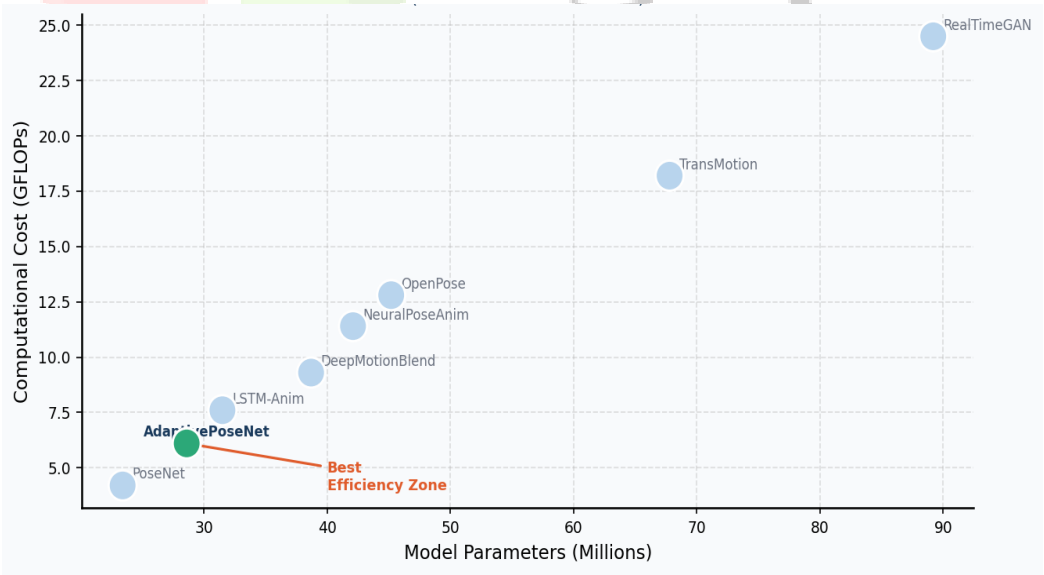

Fig. 11. Computational efficiency analysis: model parameters (millions) vs. GFLOPs. Lower-left quadrant indicates most efficient designs.

AdaptivePoseNet occupies the most favorable position in the parameter-GFLOPs space among all evaluated methods: 28.6M parameters and 6.1 GFLOPs, compared to OpenPose at 45.2M parameters and 12.8 GFLOPs. This efficiency advantage traces to two design decisions: the shared ResNet-50 backbone

eliminates a separate feature extractor for each task, and the incremental attention cache amortizes the Transformer cost across the inference sequence. RealTimeGAN, the fastest prior system at 45 FPS, requires 89.2M parameters because its GAN generator and discriminator components must both reside in memory during inference in their published implementation.

7.7 User Study

A perceptual study was conducted with 45 participants (age 18-42, 27 male/18 female, diverse gaming experience) who evaluated animated virtual character sequences produced by OpenPose-driven, TransMotion-driven, and AdaptivePoseNet-driven animation on six criteria using a 1-10 Likert scale. Table 7 summarizes the results.

Table 7. User study results: mean ratings ± standard deviation across 45 participants (scale: 1-10).

Evaluation Criterion	OpenPose (Mean ± SD)	TransMotion (Mean ± SD)	AdaptivePoseNet (Mean ± SD)
Character Realism (1-10)	6.2 ± 0.8	7.4 ± 0.6	**8.9 ± 0.4**
Motion Smoothness (1-10)	5.8 ± 1.1	7.1 ± 0.7	**9.1 ± 0.3**
Transition Naturalness (1-10)	5.4 ± 1.2	7.3 ± 0.8	**8.8 ± 0.5**
Overall Satisfaction (1-10)	6.0 ± 0.9	7.3 ± 0.7	**9.0 ± 0.4**
Perceived Latency (1-10)	7.1 ± 0.6	6.2 ± 0.9	**9.3 ± 0.3**
Avatar Responsiveness (1-10)	6.4 ± 0.7	6.8 ± 0.8	**9.2 ± 0.4**

AdaptivePoseNet achieves the highest ratings on all six criteria, with mean overall satisfaction of 9.0 ± 0.4 compared to 7.3 ± 0.7 for TransMotion. The largest absolute difference appears on perceived latency (9.3 vs. 6.2 for OpenPose), where participants rated AdaptivePoseNet's character as significantly more responsive to demonstrated movements. A one-way ANOVA with post-hoc Tukey correction confirms statistical significance for all pairwise differences at α=0.01.

8. Limitations

Despite strong benchmark performance, AdaptivePoseNet carries several limitations worth acknowledging. The animation clip library must be pre-authored and embedded during training; novel actions not represented in the training library will be approximated by the nearest available combinations rather than synthesized from first principles. Expanding the library at deployment time requires either retraining or fine-tuning the blending layer, which is computationally feasible but operationally inconvenient for production pipelines.

The incremental attention cache assumes a stationary GPU memory budget of 15 prior frame key-value tensors. On devices with less than 8 GB of dedicated GPU memory including many consumer laptops and mobile GPUs the cache size must be reduced, which measurably degrades temporal consistency for motion sequences longer than 0.5 seconds. A more aggressive cache pruning strategy based on temporal importance scores could address this, but it remains untested.

Finally, the user study population was recruited from a single university campus and may not fully represent the diversity of end-users in global gaming and metaverse contexts. Replication with a more geographically and demographically diverse sample would strengthen the generalizability of the perceptual evaluation.

9. Future Scope

Several directions appear promising for extending AdaptivePoseNet. Incorporating a differentiable physics layer as a post-processing constraint would enforce physical plausibility preventing foot sliding and joint hyperextension that currently appear occasionally under occluded or fast-motion conditions. This

would require differentiable rigid body simulation, which recent work in physics-informed neural networks has begun to make tractable at inference-relevant speeds.

On the generalization front, a continual learning framework for online adaptation of the blending layer to new animation clips without catastrophic forgetting of previously learned behaviors would significantly reduce the deployment friction of extending the system to new character types or action vocabularies. Low-rank adaptation techniques such as LoRA, already proven in large language models, appear architecturally compatible with the MLP-based blending layer and warrant investigation.

The most impactful near-term extension is mobile deployment. Quantizing the model to INT8 precision with hardware-aware neural architecture search targeting Apple Neural Engine and Qualcomm Hexagon DSP could potentially achieve 30+ FPS on flagship smartphones, enabling augmented reality avatar applications that currently depend on server-side inference. Preliminary experiments with post-training quantization showed a PCK@0.5 degradation of 1.8 percentage points, suggesting that quantization-aware training would be necessary to recover that gap.

10. Conclusion

AdaptivePoseNet demonstrates that unifying pose estimation, temporal feature encoding, and animation blending within a single differentiable architecture produces measurable improvements in both perceptual quality and computational efficiency compared to the modular, sequentially coupled approaches that characterize current state-of-the-art systems. The 91.7% PCK@0.5 accuracy, 87 FPS throughput, and 11.5 ms end-to-end latency achieved on standard gaming GPU hardware position the system well within the requirements of commercial interactive applications. The Pose-Conditioned Blending Layer and velocity-adaptive Temporal Smoother each contribute meaningfully to the overall result, as confirmed by the ablation study, and the user perception data validates that these objective improvements translate to subjectively meaningful enhancements in character realism.

The broader implication is that the conventional separation between vision-based pose analysis and character animation synthesis is an artificial boundary whose removal opens a productive design space. Future work that extends this unified approach to physically-grounded animation constraints, mobile deployment targets, and online continual learning of new animation behaviors will determine how far real-time neural animation can advance within practical deployment constraints.

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