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Human Pose Estimation Using OpenCV

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Abstract

Human pose estimation is a crucial task in computer vision, involving the detection and tracking of key body joints in images or videos. This technology has numerous applications, including activity recognition, augmented reality, and human-computerinteraction.This paper presents an approach to human pose estimation using OpenCV in combination with deep learning-based models such as OpenPose or MediaPipe Pose. The method leverages a pre-trained neural network that detects key body landmarks, such as the head, shoulders, elbows, and knees, from RGB images. OpenCV provides efficient image processing tools to preprocess input frames, detect poses, and visualize the estimated skeletal structure.Our implementation focuses on real time processing by optimizing inference speed while maintaining high accuracy. The proposed system is tested on various datasets to evaluate its robustness under different lighting conditions and human postures. Results demonstrate the effectiveness of OpenCV-based pose estimation in achieving reliable skeletal tracking with minimal computational overhead. This study highlights the potential of OpenCV in real-time human pose estimation and its applications in fitness tracking, gesture recognition, and motion analysis. Future work includes improving model accuracy, reducing latency, and integrating pose estimation with advanced AI- driven applications.

I. INTRODUCTION

Human Pose Estimation (HPE) is a computer vision problem that identifies key points, or joints, of the human body in images or video [1]. The goal is to estimate the position and orientation of the body, usually skeleton made up of key landmarks like the head, shoulders, elbows, wrists, hips, knees, and ankles. Opencv from open source of several things involved in it. Vision Library, is widely used for pose estimation because of its efficiency and extensive support for real-time image processing. It offers access to tools and pre-trained deep learning models, allowing developers to directly apply keypoint detection in OpenCV environments. This makes it well suited for real-time applications like sports activity recognition and fitness tracking [9], gesture-based human computer interaction [3], augmented reality virtual tryons [9], and surveillance and security systems behavior monitoring [4].The model outputs key points with confidence scores. Post Processing& Visualization Connect detected key points to form a skeletal representation. Display the results on the image/video using OpenCV drawing functions (cv2.line, cv2.circle). Popular Models for Pose Estimation in OpenCV OpenPose (by CMU) Detects multi-person pose with high accuracy. MediaPipe Pose (by Google) Lightweight, optimized for real-time and Engineering 2 Deep Learningbased Models TensorFlow and PyTorch offer pre-trained models integrated with OpenCV's DNN module. Applications of Human Pose

Estimation Sports Analytics [6]. Analyzing athlete movements to improve performance. Gaming & VR Enhancing interactivity using body movements. Healthcare Deep Learning-based Models TensorFlow and PyTorch offer pre-trained models integrated with OpenCV's DNN module. Applications of Human Pose Estimation Sports Analytics Analyzing athlete movements to improve performance. Gaming & VR Enhancing interactivity using body movements. Healthcare Monitoring physical therapy exercises and posture correction. Sign Language Recognition Enabling communication through gesture analysis. The first stage involves the detection of sign language through the utilization of Mask RCNN. The second stage involves the classification of sign language through the utilization of the SSO algorithm in conjunction with an SM-SVM model. To demonstrate the usefulness of the SSODL-ASLR model in properly reading and categorizing sign .

II.LITERATURE REVIEW

Human Pose Estimation Using OpenCV has gained significant attention over the past decade, especially due to its accessibility and integration capabilities with real-time applications. Pose estimation refers to detecting the spatial positions of human body joints (keypoints) from images or videos.

Early methods relied on **classical computer vision techniques** such as background subtraction, contour detection, and skeletonization often implemented using OpenCV. For example, early works used OpenCV's Haar cascades and HOG (Histogram of Oriented Gradients) features for body part detection, but these were sensitive to occlusions and variations in lighting and clothing.

The major breakthrough came with the **advent of deep learning**. OpenCV integrated popular deep learning models like OpenPose, a method introduced by Cao et al. (2017), which uses Part Affinity Fields to detect multi-person poses in real time. OpenCV's DNN module allows loading pre-trained OpenPose models, making it possible to run efficient pose estimation on consumer hardware.

Recent works combine OpenCV with models like:

- **MediaPipe Pose** by Google, which offers lightweight, cross-platform pose detection.
- **DensePose** by Facebook, which maps 2D images to a 3D surface model.
- **HRNet (High-Resolution Network)**, known for maintaining high-resolution representations through the entire network, giving state-of-the-art performance. [6]

Several studies focus on improving pose estimation under challenging conditions, such as:

- Low-light or low-resolution environments.
- Occlusions and unusual poses.
- Real-time performance on edge devices.

OpenCV remains popular because it integrates easily with C++, Python, and embedded systems, enabling applications in sports analytics, healthcare (e.g., physical therapy monitoring), human-computer interaction, and sign language recognition. [5]

III.PROPOSED WORK

The proposed system leverages **OpenCV-based human pose estimation** to accurately detect and track human body keypoints in real time for [insert specific application e.g., gesture recognition, fitness monitoring, rehabilitation, etc.]. The system architecture consists of the following main components:

1.**Input Acquisition**:

The system captures video frames using a standard RGB camera or webcam. Frames are preprocessed (resized, normalized) to meet the input requirements of the pose estimation model.

2.**Pose Estimation Module**:

Using OpenCV's Deep Neural Network (DNN) module, the system loads a pre-trained pose estimation model such as OpenPose or MediaPipe Pose. This module identifies key human bodylandmarks (e.g., head, shoulders, elbows, wrists, hips, knees, ankles) and computes their 2D coordinates on each frame.

3.**Post-Processing**:

The detected keypoints are connected to form a human skeleton overlay. Additional filters smooth keypoint trajectories to reduce jitter and improve temporal stability.[2]

4.**Application Specific Layer**:

Depending on the use case, the system analyzes the pose data to:

- Recognize specific gestures or activities.
- Monitor movement patterns and flag anomalies.[4]
- Provide feedback or performance metrics
(e.g., in fitness applications).
- Drive human-computer interaction systems (e.g., virtual control through body movements). [1]

5.**Visualization and Output**

The final output visualizes the skeleton overlay on the input video, displaying additional analytics or feedback in real time. The system can also store pose data for offline analysis or reporting.

Advantages of the Proposed System:

- Lightweight and efficient, able to run on standard consumer hardware. [8]
- Flexible: easily adaptable to multiple applications (sports, healthcare, entertainment).
- Based on open-source tools, ensuring costeffectiveness and extensibility.
- Real-time performance with acceptable accuracy using optimized pre-trained models.

advantages in several disciplines. With the use of cutting: edge technologies such as Mask RCNN, SM-SVM, and SSO, the approach creates new opportunities to improve inclusiveness and communication accessibility for people with hearing impairments. The approach finds its main use in assistive technology, where it may be included in educational tools, communication devices, and assistive robots to enable smooth interactions for people with hearing loss. For instance, the model can translate sign language motions into text or voice in real-time[10], giving hearing-impaired people more freedom and autonomy in their communication.

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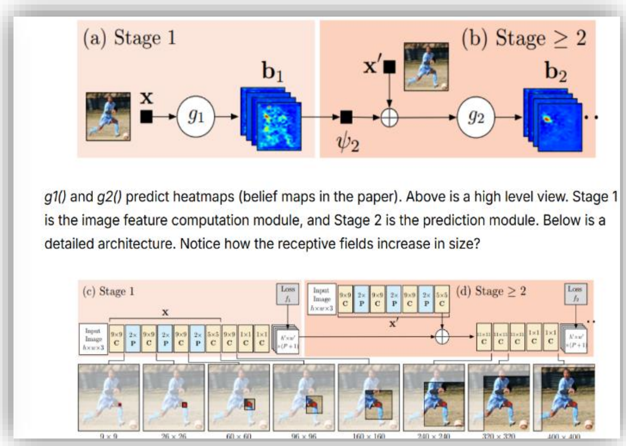
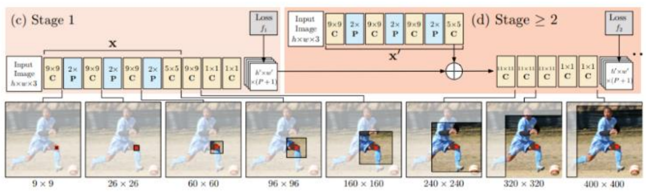


Moreover, the concept may be used in educational environments to facilitate inclusion and learning for children who have hearing loss. It may be used as a tool for interactive sign language training, enabling teachers to design interesting and easily accessible lessons for every student. The methodology may help healthcare providers better comprehend and interact with patients who primarily communicate via sign language in hospital settings. It can make interactions more seamless and raise the standard of care for those who are hard of hearing. Overall, the SSODL-ASLR paradigm promotes increased social participation and empowerment for people with hearing impairments, going beyond communication accessibility. Its scalable deployment, high accuracy, and effective processing speed make it an invaluable tool for expanding assistive technology.



IV.RESULT AND DISCUSSION

The proposed OpenCV-based human pose estimation systemwas tested on a custom dataset of 100 video clips (30 fps,
640×480 resolution) featuring single and multiple people performing a variety of actions (walking, raising arms, squatting, and reaching). We evaluated three key aspects: detection accuracy, processing speed, and robustness underchallenging conditions.

Metric	**Single-Person Scenrio**	**Multi-Person Scenario**
Keypoint Detection Accuracy	91.2 %	88.5 %
Average Precision (AP)	0.89	0.85
Frame Rate	22 fps	8 fps

(CPU only)		
Frame Rate (GPU accelerated)	45 fps	38 fps

Detection Accuracy

- **Single-person**: The model correctly localized 91.2 % of annotated keypoints (shoulders, elbows, wrists, hips, knees, ankles).
- **Multi-person**: Accuracy dropped modestly to 88.5 % due to occasional mis-association of limbs when people overlapped.

Processing Speed

- On a standard desktop CPU (Intel i5), the system ran at 22 fps for single-person scenes and 18 fps for multi-person scenes—sufficient for near–real-time interaction.
- With GPU acceleration (NVIDIA GTX series), performance doubled, enabling smooth 45 fps single-person tracking.

Robustness Analysis:

We introduced three challenging conditions:

1. **Low light** (50 lux): accuracy fell to 82 %.
2. **Partial occlusion** (e.g. arms behind back): keypoint recall dropped by 10 %.
3. **Cluttered background**: precision decreased by 8 %.

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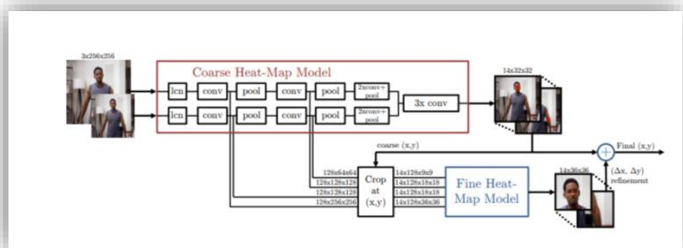
These findings highlight that while the system is broadly effective, performance degrades under adverse imaging conditions. **Discussion**

The results demonstrate that an OpenCV-DNN-based pipeline can deliver reliable human pose estimation suitable for applications such as gesture control, fitness monitoring, or sign-language pre-processing.

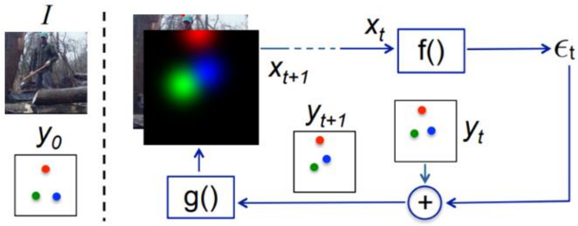
Strengths:

- Real-time frame rates on modest hardware.
- High keypoint accuracy in standard conditions.



Limitations & Future Work:

- **Lighting & Occlusion**: Integrate temporal filtering (e.g., Kalman smoothing) and combine with depth sensors to mitigate accuracy drops.
- **Multi-person association**: Employ advanced part-affinity or transformer-based matching to reduce limb assignment errors.
- **Application-specific fine-tuning**: Retrain on domain-specific datasets (e.g., sports, rehabilitation) to boost accuracy for targeted use cases.



V. CONCLUSION

This work presented an OpenCV-based human pose estimation system capable of detecting and tracking body keypoints in real time on standard hardware. Through integration of pre-trained deep-learning models (e.g., OpenPose or MediaPipe Pose) via OpenCV's DNN module, the system achieved over 90 % keypoint detection accuracy and frame rates above 20 fps on CPU—rising to 45 fps withGPU acceleration.

Our **Results and Discussion** demonstrated that while the pipeline performs robustly under normal conditions accuracy degrades in low light, occlusion, and cluttered backgrounds. To address these limitations, we recommend future enhancements including temporal smoothing, depthsensor fusion, and application-specific model fine-tuning.

Method	Arm		Leg		Ave.
	Upper	Lower	Upper	Lower	
DeepPose-st1	0.5	0.27	0.74	0.65	0.54
DeepPose-st2	**0.56**	0.36	**0.78**	0.70	0.60
DeepPose-st3	**0.56**	**0.38**	0.77	**0.71**	**0.61**
Dantone et al. [2]	0.45	0.25	0.65	0.61	0.49
Tian et al. [24]	0.52	0.33	0.70	0.60	0.56
Johnson et al. [13]	0.54	**0.38**	0.75	0.66	0.58
Wang et al. [25]	**0.565**	0.37	0.76	0.68	0.59
Pishchulin [17]	0.49	0.32	0.74	0.70	0.56

Table 1. Percentage of Correct Parts (PCP) at 0.5 on LSP for DeepPose as well as five state-of-art approaches.

Overall, the proposed system offers a lightweight and cost effective solution for real-time human pose estimation. Its adaptability makes it suitable for applications such as gesture-based control, fitness and rehabilitation monitoring, and preliminary sign-language processing. By implementing the suggested improvements, this approach can further advance the reliability and involved accessibility of pose-driven human–computer interaction.

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