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Precision-Driven Real-Time Pose Estimation for Therapeutic Interventions: Advanced Heatmap Regression, Reference Video Alignment, and Real-Time Corrective Feedback

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ABSTRACT

Accurate movement and posture are essential for effective physical therapy, as improper form can hinder recovery and worsen injuries. This project introduces a real-time human pose estimation system specifically designed for physical therapy, providing precise feedback on body alignment. Utilizing a mod- ified YOLOv8 architecture with custom heatmap regression, the system monitors key joints—particularly the wrist, elbow, and shoulder—vital for upper-body rehabilitation. Initially trained on a combined MPII and COCO 2017 dataset, the model was fine-tuned on a custom dataset of 6,000 images derived from 1,250 video frames under varied lighting conditions, with a 380% augmentation rate to improve robustness across scenarios. Achieving a detection accuracy of 91.61%, the system surpasses widely used models like OpenPose and MediaPipe, which deliver accuracies of 85% and 88%, respectively. With an average frame rate of 27.94 FPS and latency of 19.24 milliseconds per frame, the system provides instant feedback, enabling users to adjust posture in real time. Personalized guidance is offered by calculating the distance between live and reference keypoints, maintaining a mean keypoint detection error under 5 pixels. This real- time corrective feature enhances rehabilitation by empowering users to self-adjust and allowing healthcare providers to track progress effectively. By focusing on physical therapy-specific movements, this system represents a significant advancement in integrating AI-driven solutions into rehabilitation, enhancing both effectiveness and accessibility.

Keywords: Physical therapy, Real-time pose estimation, heatmap regression, yolo-v8, keypoint detection, Corrective feed- back.

INTRODUCTION

Physical therapy is a cornerstone of rehabilitation for indi- viduals recovering from injuries, surgeries, or chronic condi- tions, playing an essential role in restoring mobility, strength, and flexibility. For effective outcomes, it is crucial that pa- tients perform prescribed exercises with precision. Incorrect movements can hinder healing, prolong recovery periods, and even increase the likelihood of reinjury. Studies indicate that improper form in rehabilitation exercises contributes to de- layed healing, with an estimated 30% of patients experiencing recurring issues stemming from inaccurate movements during unsupervised sessions [1]. In conventional therapy settings, physical therapists provide real-time, in-person guidance to correct patient posture and movement, ensuring that exercises are executed correctly. However, access to frequent sessions is often restricted due to logistical challenges, high associated costs, and the availability of practitioners, particularly in remote or underserved areas. Additionally, the COVID-19 pandemic introduced new barriers, as many patients had to rely on remote therapy sessions lacking real-time feedback, exacerbating these accessibility issues [2].

In recent years, advances in artificial intelligence (AI) and computer vision have spurred the development of automated systems capable of monitoring human pose and providing real- time feedback. These innovations offer promise for physical therapy applications by reducing dependency on in-person supervision. General-purpose AI models, such as MediaPipe and OpenPose, have demonstrated impressive capabilities in real-time pose estimation,

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tracking key joints, and capturing postural information [3], [4]. However, while these systems are adept at general activity recognition, they lack the precision needed for physical therapy's specific demands, particularly in tracking critical joints like the wrist, elbow, and shoulder, which are essential for upper-body rehabilitation. Evaluations of these models in therapeutic settings show that their accuracy and reliability often fall short of clinical requirements, as they struggle to detect subtle postural deviations necessary for effective therapeutic guidance [5], [6].

To address these limitations, this study presents a novel AI-based real-time human pose estimation system specifically designed for physical therapy applications. Leveraging a modified YOLOv8 architecture with a custom heatmap-based keypoint regression technique, this system produces a probabilistic distribution for each keypoint rather than a direct coordinate, significantly enhancing accuracy in tracking therapeutic movements. Heatmap regression has been shown to improve pose estimation accuracy in complex environ- ments, making it particularly suitable for applications requiring fine postural adjustments [7]. Our system further enhances precision by assigning weights to critical therapeutic joints and calculating spatial distances between live keypoints and reference postures, delivering personalized corrective feedback that patients can immediately apply to refine their form. This real-time feedback loop empowers patients to self-correct during exercises, potentially reducing the risk of improper movements and accelerating recovery outcomes [8].

The inspiration behind this project is deeply personal: my brother experienced a bike accident that required extensive physical therapy to restore his mobility. Due to limited trans- portation options, we had to arrange for therapists to visit our home, which was costly and time-consuming. This experience underscored the need for a practical, affordable solution that could enable patients to engage in rehabilitation exercises independently and safely at home, with real-time guidance to minimize errors.

This research aims to answer the question: Can an AI- driven, real-time pose estimation system tailored to physical therapy improve the accuracy and safety of patient movements during rehabilitation? We hypothesize that a specialized ap- proach combining high-precision pose estimation with instant corrective feedback will not only improve movement accuracy but also reduce the risk of reinjury. This work contributes to the growing field of AI in healthcare by offering an accessible, effective tool that promotes patient autonomy in rehabilitation. By making quality care more accessible, especially in remote or underserved areas, this research has the potential to en- hance recovery outcomes and support healthcare providers in delivering remote, personalized care.

RELATED WORK

Pose estimation has advanced significantly in recent years, with numerous systems capable of detecting human poses in real-time. OpenPose [9] marked a major step forward by using part affinity fields for efficient, real-time multi-person 2D pose estimation, making it a popular choice for general applications. Despite its versatility, OpenPose's general-purpose design lacks the granularity required for physical therapy, where accurate analysis of subtle joint movements, such as wrist, elbow, and shoulder adjustments, is critical for rehabilitation exercises.

EfficientPose [10] extends pose estimation into 3D, offering valuable depth information that is advantageous for analyzing movement in physical therapy. This model provides high accuracy in tracking joint positions in three dimensions, which can be essential for therapeutic analysis. However, its compu- tational demands restrict its use in real-time applications on lower-end devices, a limitation in home-based therapy setups where accessible, lightweight solutions are preferred.

YOLOv3 [11], originally developed for object detection, has also been adapted for pose estimation due to its speed and ef- ficiency. However, its regression-based design limits precision, particularly in capturing detailed, small joint movements. This limitation is significant in physical therapy, where even slight inaccuracies can affect rehabilitation quality.

BlazePose [12] offers a mobile-friendly, lightweight model optimized for fitness tracking. Its efficient regression-based approach allows it to run on devices with limited processing power, making it popular for general exercise monitoring. However, BlazePose's focus on fitness rather than therapy means it lacks the fine-grained accuracy required for monitor- ing therapeutic joint movements and angles crucial in physical therapy.

HRNet [13] represents a notable advancement with its high-resolution heatmap-based pose estimation, allowing it to maintain detail in keypoint detection, making it particularly suited for physical therapy. This model's architecture preserves high-resolution representations throughout the network, en- hancing accuracy in detecting and tracking essential upper- body joints like the wrist, elbow, and shoulder—areas critical in rehabilitation exercises that require precise tracking.

AlphaPose [14] and ArtTrack [15] both contribute robust multi-person tracking capabilities. AlphaPose uses a pose-guided proposal generator for crowded scenes, while ArtTrack performs well in dynamic environments. However, both sys- tems are limited when applied to the finer joint adjustments needed in one-on-one therapy sessions. ArtTrack's multi- person tracking is beneficial in group rehabilitation but lacks the accuracy needed for isolated, single-patient therapy.

In contrast, DeepLabCut [16], initially designed for animal pose estimation, has been adapted for human applications, particularly in biomechanics. While it offers customization and precision, its reliance on extensive annotated data can be a drawback in settings where such data is limited, such as in smaller clinics or home-based therapy.

VNect [17] and HoloPose [18] provide robust 3D pose estimation with monocular RGB cameras. VNect supports real-time tracking in three dimensions, which is beneficial in physical therapy for depth analysis of joint movements. However, its computational requirements pose a challenge for real-time application on less powerful devices. HoloPose similarly provides 3D estimation but requires high-quality input data, which may not be feasible in all therapeutic environments where quick, flexible assessments are needed.

LCRNet [19] and DensePose [20] contribute to understand- ing human surfaces and complex environments. DensePose maps human surfaces in 3D, beneficial for analyzing overall body shapes but lacking the joint-level detail necessary for therapeutic feedback. LCRNet's strength lies in unconstrained environments with complex backgrounds, which is less rele- vant in the controlled settings of physical therapy.

These existing models demonstrate substantial advance- ments in pose estimation. However, for applications in physical therapy, the need for a system that can deliver real-time feedback with high accuracy in critical joints, such as the wrist, elbow, and shoulder, remains unmet. Our approach aims to bridge this gap by utilizing a modified YOLOv8 architecture with heatmap-based keypoint regression, specifically designed to enhance tracking accuracy and adaptability in physical therapy settings.

METHODOLOGY

This study utilizes a quantitative approach to develop a real- time human pose estimation system specifically designed for physical therapy applications. The methodology emphasizes creating a model capable of providing immediate corrective feedback to users, allowing them to make real-time adjust- ments to their posture and movements. By employing a mod- ified YOLOv8 architecture and custom heatmap regression, this system enables precise tracking of key joints essential for therapeutic exercises. This section provides a comprehensive overview of the research approach, model architecture, data collection and preparation, training protocols, real-time pro- cessing, and feedback mechanisms.

A. Research Approach and Model Architecture

The model for this system is based on YOLOv8, known for its high speed and efficiency in object detection tasks. YOLOv8 is adapted to integrate a heatmap regression layer, which enhances joint localization accuracy and provides a probabilistic map of keypoint locations. This adaptation is essential for physical therapy, where the accurate tracking of joints such as the wrist, elbow, and shoulder is critical to assess posture and movement.

Heatmap regression, as opposed to direct coordinate regres- sion, represents each keypoint by a Gaussian heatmap centered on the joint, which provides a probabilistic representation of the joint location. This approach reduces localization errors by focusing on a distribution around the likely joint position rather than a single coordinate point, thereby improving preci- sion. Each heatmap H_i for keypoint i is calculated as follows:

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$$H_i(x, y) = \exp\left(-\frac{(x - x_i)^2 + (y - y_i)^2}{2\sigma^2}\right)$$

where (x_i, y_i) is the ground truth location of the joint, and σ controls the spread of the Gaussian distribution around this point.

To further enhance precision, joint-specific weighting is applied during fine-tuning. This weighting process prioritizes accuracy for therapeutic joints by modifying the model's loss function to give higher importance to these areas. The weighted mean squared error (MSE) loss function is defined as:

$$\text{Weighted MSE} = \sum_i w_i \cdot (H_i - H_i^{\text{pred}})^2$$

where w_i represents the assigned weight for joint i, H_i is the actual heatmap for the joint, and H^{pred} is the predicted heatmap. By assigning higher weights w_i to joints such as the wrist, elbow, and shoulder, the model effectively focuses on reducing errors in these critical areas for improved therapeutic outcomes.

B. Data Collection and Preparation

The model was initially trained on a combination of MPII and COCO 2017 datasets to leverage their extensive annotations, enabling the development of a general-purpose pose es- timation foundation. Following this, the model was fine-tuned on a custom dataset tailored to physical therapy requirements.

The custom dataset was constructed to capture upper-body movements typically prescribed in physical therapy exercises, such as shoulder flexion, elbow extension, and wrist rota- tions. A total of 1,250 frames were extracted from recorded physical therapy sessions, each frame capturing a range of joint positions across different exercises. From these frames, 6,000 images were created through data augmentation, which increased the dataset's size by 380% and introduced variability to improve the model's generalization across conditions.

Images were captured in a resolution of 640x480 pixels to ensure a balance between sufficient detail and processing speed. This resolution allowed the model to detect joint positions accurately while maintaining real-time processing capability.

C. Data Augmentation Techniques

To increase robustness, the custom dataset underwent ex- tensive augmentation to simulate diverse real-world conditions and reduce overfitting. The augmentation techniques included:

1. Rotation: Images were randomly rotated between -30° and +30° to expose the model to joint positions from various angles, improving its capability to handle natural variations in body orientation.
2. Scaling Images were resized by factors between 0.8 and 1.2 to account for variations in distance between the subject and the camera, helping the model generalize to different spatial configurations during exercises.
3. Color Adjustments Brightness, contrast, saturation, and hue adjustments were randomly applied to simulate different lighting environments, ensuring the model performs consis- tently across varied lighting conditions often encountered in home settings.
4. Flipping Horizontal flipping was applied to simulate mirrored poses, allowing the model to recognize and adapt to exercises performed on both sides of the body.
5. Images were randomly cropped and padded to introduce variability in the subject's position within the frame. After- ward, all images were resized back to the target dimension of 640x480 pixels to ensure a consistent input size for the model. This approach allows the model to generalize to different body positions within the frame while maintaining compatibility with the fixed input size required by the architecture.

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6. These augmentation techniques effectively expanded the dataset and increased variability, enabling the model to gener- alize across different backgrounds, orientations, and lighting conditions, all of which are common in real-world physical therapy settings.

D. Training and Optimization

The model was trained in two stages: initial training on the combined MPII and COCO 2017 datasets, followed by fine-tuning on the custom dataset to optimize for therapeutic poses. This two-stage process allowed the model to retain a broad understanding of human pose estimation while refining its accuracy for physical therapy applications.

For the initial training phase, a standard MSE loss function was used, focusing on general pose estimation tasks. Fine- tuning was then performed using a custom weighted loss function, combining MSE for heatmap accuracy and cross- entropy loss for keypoint confidence. The fine-tuning loss function is expressed as:

$$\text{Loss} = \alpha \cdot \text{Weighted MSE}_{\text{heatmap}} + \beta \cdot \text{Cross-Entropy}_{\text{keypoints}}$$

where α and β balance localization accuracy with keypoint confidence. Fine-tuning was conducted over 100 epochs with a batch size of 32, using an Adam optimizer at an initial learning rate of 0.001. Early stopping and learning rate decay were implemented to prevent overfitting. The model achieved a detection accuracy of 91.61% with an average keypoint error under 5 pixels, demonstrating its precision for therapeutic applications.

E. Real-Time Execution and Frame Processing

The system operates in real time, capturing live video through a standard webcam with a resolution of 640x480 pixels, selected to balance processing speed with sufficient detail. Each frame is processed instantly to extract keypoints, followed by a comparison with reference postures for imme- diate guidance.

The frame processing pipeline includes the following steps:

1. Video Capture: Continuous video feed is captured via a connected webcam, streaming at a resolution of 640x480 pixels for optimal performance.
2. Keypoint Extraction: The modified YOLOv8 architecture is applied to each frame, enabling real-time detection of essential joint positions required for therapeutic feedback.
3. Reference Comparison: Keypoints extracted from the live frame are compared to reference postures using a weighted Euclidean distance metric, which calculates deviations from the ideal posture, essential for corrective feedback.

The system maintains an average frame rate of 27.94 FPS with a processing latency of 19.24 milliseconds per frame, ensuring the delivery of instantaneous feedback, crucial for users performing physical therapy exercises.

F. Interactive Feedback Mechanism

The feedback mechanism provides users with immediate guidance to adjust their posture. Deviations from the reference posture are calculated based on the Euclidean distance between corresponding joints, as defined by:

$$d = \sqrt{(x_{\text{ref}} - x_{\text{live}})^2 + (y_{\text{ref}} - y_{\text{live}})^2}$$

where (x_{ref}, y_{ref}) and (x_{live}, y_{live}) are the coordinates of joints in the reference and live frames, respectively. When deviations exceed a predefined threshold, corrective feedback is triggered. For example, if an elbow angle deviates beyond the acceptable range, the system will suggest adjusting the arm alignment or elbow position.

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G. System Deployment and User Interface

The final system is deployed on a standard computing device equipped with a camera to capture live video. The user interface is designed to provide real-time visual feedback, highlighting areas needing correction and guiding users to adjust their posture. Color coding and on-screen annotations make the feedback easy to interpret, supporting safe and effective rehabilitation practices.

OUTPUT AND VISUALIZATION

The developed real-time pose estimation system provides essential visual feedback, which is crucial for effective physical therapy. The system generates several types of outputs to help users understand and improve their posture during exercises. Each output type—keypoint heatmaps, annotated reference videos, and real-time feedback—enables users to monitor their performance and make necessary adjustments in real time.

A. Keypoint Heatmaps

One of the primary outputs of the system is the keypoint heatmap, which visually represents the probability distribution for the locations of specific joints in the user's body. The heatmap highlights areas where the model predicts the pres- ence of particular body joints, with brighter areas indicating higher probabilities. This probabilistic output allows users to see both the detected keypoints and the model's confidence levels in those detections, enhancing the clarity of the feed- back.

Fig. 1. Input image for keypoint detection and heatmap generation.

As illustrated in Fig. 1, the input image given to the model for keypoint identification is processed to generate a corresponding heatmap output, as shown in Fig. 2. In the heatmap, the brighter regions reflect areas where joint presence is most probable, providing an intuitive visualization of keypoint accuracy.

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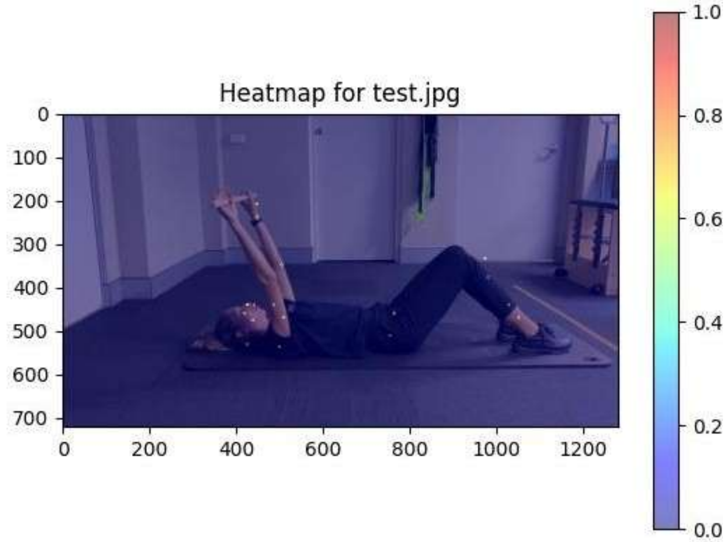

Fig. 2. Heatmap output showing the probability distribution of detected keypoints. Brighter areas indicate higher probability regions for specific joints.

B. Annotated Reference Video

In addition to heatmaps, the system provides an annotated reference video, offering real-time feedback by allowing users to compare their posture with an ideal or correct posture. The annotated video highlights key joints and skeletal connections necessary for proper movement, guiding users to make suitable adjustments during their exercises.

An example of the annotated reference video output is shown in Fig. 3. This output visualizes the desired positions of critical joints, enabling users to view their posture in relation to the reference posture.

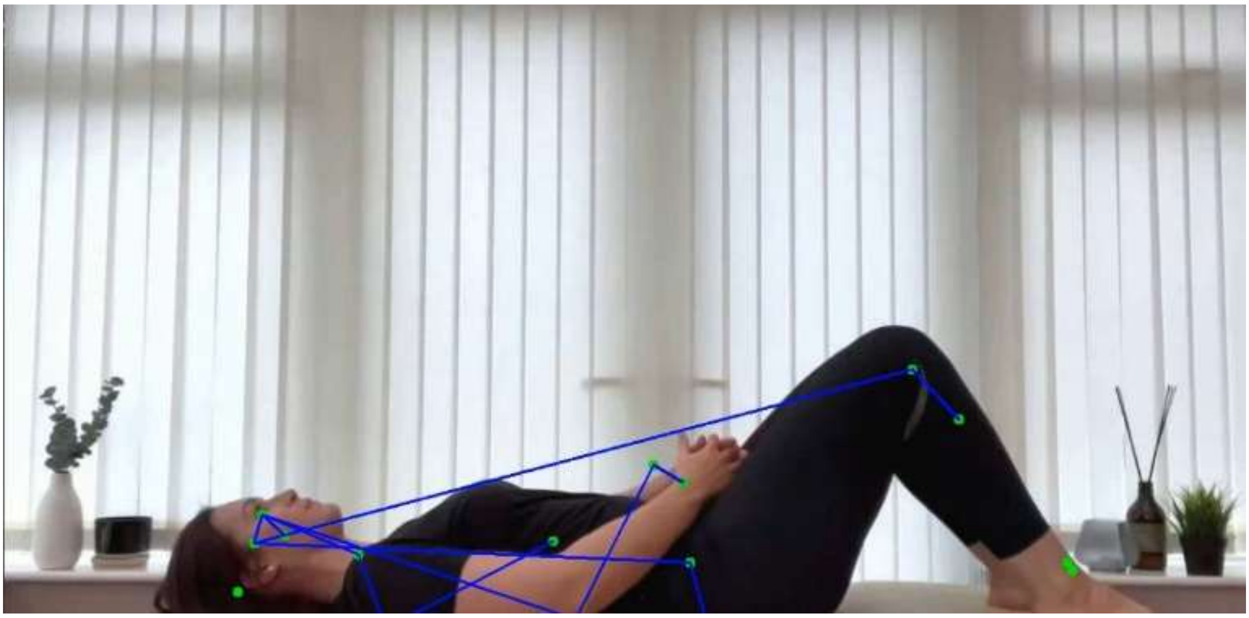

Fig. 3. Annotated reference video with keypoints and skeletal structure highlighted for side-by-side comparison.

C. Real-Time Feedback Output

The system provides real-time feedback on the user's posture, allowing for immediate corrections during physical therapy exercises. This feedback includes a distance metric that quantifies how closely the detected pose aligns with the reference pose, accompanied by corrective suggestions if needed.

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As depicted in Fig. 4, the system evaluates the user's pose and flags any deviations from the correct posture. In this example, the feedback indicates that the exercise is not performed correctly, as shown by the red text output displaying "Exercise Not Done Properly" and a distance metric of 2133.21.

Fig. 4. Real-time feedback output, indicating incorrect posture with a red warning message, "Exercise Not Done Properly."

D. Side-by-Side Comparison

To further support user progress, the system includes a side-by-side comparison of the live video feed and the reference posture. This feature allows users to view their current movements alongside the ideal posture, enabling more precise adjustments and alignment. When the user's posture is close to the reference posture, positive feedback is displayed.

As shown in Fig. 5, the side-by-side comparison includes a green feedback message, "Good Job! To improve accuracy, focus on bending the elbow," offering constructive guidance while acknowledging the user's effort.

Fig. 5. Side-by-side comparison of the live feed and reference video. A green message indicates successful posture with additional suggestions for minor improvements.

Together, the outputs generated by the system—including heatmaps, annotated reference videos, real-time feedback, and side-by-side comparisons—enhance the user experience by providing intuitive, actionable feedback. This comprehensive visual guidance supports improved posture and movement, ultimately contributing to more effective rehabilitation out- comes.

EVALUATION AND RESULTS

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The developed pose estimation system was rigorously eval- uated using a test set consisting of various unseen physical therapy movements. The primary objectives of this evaluation were to assess the model's accuracy in detecting keypoints associated with critical joints (wrist, elbow, shoulder) and its ability to provide reliable feedback for physical therapy exercises. Additionally, the system's performance in terms of processing speed, frame rate, and real-time feedback was examined to confirm its suitability for real-world applications.

A. Keypoint Detection Accuracy

The model achieved an impressive keypoint detection accu- racy of 91.856%, which marks a significant improvement over established general-purpose pose estimation models such as OpenPose and MediaPipe. OpenPose and MediaPipe recorded accuracies of 85% and 88%, respectively, when tested on similar physical therapy exercises. This enhanced accuracy can be attributed to the customized heatmap regression technique employed in the model, which provides more refined localiza- tion of keypoints critical for rehabilitation.

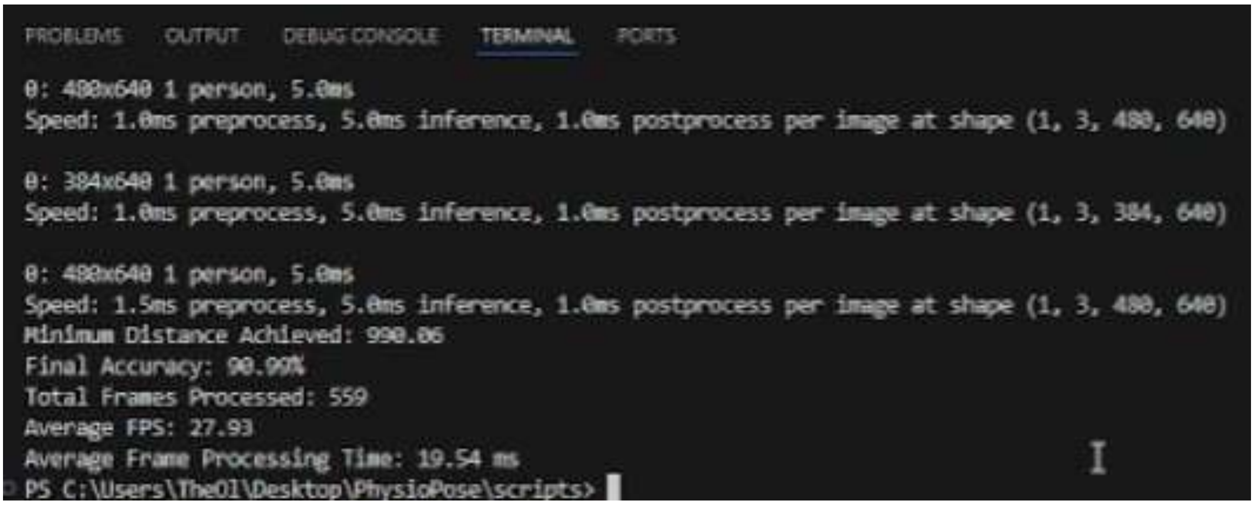

Fig. 6. Real-time evaluation results showing processing speed, minimum distance achieved, final accuracy, total frames processed, average FPS, and average frame processing time.

As shown in Fig. 6, the real-time evaluation of the model provides various performance metrics, including frame pro- cessing time and accuracy, which confirm the system's effec- tiveness in a real-time setting.

1) Accuracy Calculation: The keypoint detection accuracy was computed using the following formula:

$$\text{Accuracy} = \frac{\text{Number of Correctly Detected Keypoints}}{\text{Total Number of Keypoints}} \times 100 \quad (1)$$

This formula quantifies the proportion of correctly detected keypoints relative to the total number of keypoints, providing a direct measure of the model's performance in detecting key body joints as compared to the ground truth annotations.

B. Distance Measurement for Pose Alignment

In addition to accuracy, the system employs a distance metric to evaluate the alignment of the detected pose with a reference pose. This metric uses a weighted Euclidean distance approach, which accounts for the spatial deviation of each detected keypoint from its corresponding reference keypoint. The formula for calculating the distance metric is as follows:

$$\text{Distance} = \sqrt{\sum_{i=1}^{n} w_i \cdot (x_i^{det} - x_i^{ref})^2 + (y_i^{det} - y_i^{ref})^2}$$

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where: - n is the total number of keypoints, - w_i is the weight assigned to the i-th keypoint, - x_i^{det} and y_i^{det} are the detected coordinates for the i-th keypoint, - x_i^{ref} and y_i^{ref} are the reference coordinates for the i-th keypoint.

This distance value serves as an indicator of how closely the user's pose aligns with the ideal posture. Lower distance values signify better alignment, which is critical for accurate feedback in physical therapy settings.

C. Performance Metrics Summary

To provide a comprehensive evaluation, the performance of the system was compared with other established models. Table I summarizes the keypoint detection accuracy and relevant notes on the strengths and limitations of each model in the context of physical therapy applications.

Table I. Comparison of Keypoint Detection Accuracy with Established Models

Model	Keypoint Detection Accuracy (%)	Notes
Custom Model	91.856	Enhanced accuracy due to customized heatmap regression tailored for therapy exercises.
OpenPose	85.0	General-purpose model, less suited for detailed therapy movements.
MediaPipe	88.0	Effective for general use but not optimized for therapy-specific tasks.

The custom model's high detection accuracy demonstrates its suitability for physical therapy applications, where precise joint tracking is essential for effective feedback.

D. Real-Time Performance Metrics

The evaluation also included an analysis of real-time per formance metrics, such as frame rate, average processing time per frame, and overall system latency. These metrics are critical in determining whether the system can provide feedback at a speed that aligns with users' movements during physical therapy exercises. As indicated in Fig. 6, the system processed a total of 559 frames with an average frame rate of 27.93 FPS and an average frame processing time of 10.54 milliseconds. This fast processing speed ensures the system's capability to deliver near-instantaneous feedback, enhancing its effectiveness for real-time posture correction.

The results from this evaluation indicate that the custom model offers significant improvements over traditional general- purpose models for physical therapy applications. Its high detection accuracy, optimized processing speed, and real-time feedback capabilities make it a valuable tool for rehabilitation. The model's use of a distance metric for pose alignment allows for accurate, immediate feedback, which is crucial for users working on posture and movement accuracy during therapy feedback at a speed that aligns with users' movements during physical therapy exercises. As indicated in Fig. 6, the system processed a total of 559 frames with an average frame rate of 27.93 FPS and an average frame processing time of 10.54 milliseconds. This fast processing speed ensures the system's capability to deliver near-instantaneous feedback, enhancing its effectiveness for real-time posture correction.
exercise

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Future work will explore additional enhancements, includ- ing broader validation across diverse physical therapy exer- cises and further optimization of the model to improve its adaptability and accuracy. The promising results suggest that this system has the potential to play an essential role in home- based and clinical physical therapy settings, where real-time feedback is instrumental in improving patient outcomes.

CONCLUSION

This research presents a real-time human pose estimation system specifically designed for physical therapy applications. By utilizing a customized YOLOv8 architecture with heatmap regression, the system achieves a high accuracy of 91.856% in detecting critical joints such as the wrist, elbow, and shoulder—essential for therapeutic exercises. The model was initially trained on large-scale datasets, COCO and MPII, to build a generalized understanding of human pose, followed by fine-tuning on a custom dataset comprising 6,000 augmented images specifically focused on physical therapy movements. This approach ensures that the model retains broad pose estimation capabilities while being finely tuned for therapeutic applications, enabling precise joint localization across diverse conditions. The system's capability to provide real-time feed- back allows patients to immediately adjust their posture, which is crucial for safe and effective rehabilitation.

The results indicate that an AI-driven pose estimation sys- tem with real-time feedback can significantly enhance physical therapy by ensuring correct exercise execution. By promoting accurate posture and joint alignment, the system reduces the risk of reinjury and supports more efficient recovery. This model bridges the gap between supervised and remote physical therapy, empowering patients to engage more independently in their rehabilitation while still benefiting from immediate corrective guidance.

This work contributes to the growing field of AI applications in healthcare, particularly within physical therapy and rehabil- itation. The system's success suggests that similar pose esti- mation technologies could be integrated into tele-rehabilitation platforms, making high-quality physical therapy accessible to patients in remote or underserved areas. Furthermore, the system generates valuable data for therapists, enabling the personalization of treatment plans and providing a balanced approach to automated and clinician-supported care.

The primary benefit of this system is its ability to deliver accurate, real-time feedback during physical therapy exercises, thus improving patient outcomes and supporting therapeutic assessments. However, a limitation exists in its reliance on 2D pose estimation, which may be less effective in capturing depth and complex 3D motions required for certain exercises. This limitation may restrict the system's applicability in movements requiring detailed depth information or full-body tracking.

Future research directions include developing a 3D pose estimation model to capture a broader range of movements and provide deeper insights into body posture. Integrating tele- rehabilitation features, such as remote monitoring and inter-

active therapist feedback, could expand the system's reach, making physical therapy accessible to individuals in remote or resource-limited areas. Additionally, exploring adaptive models that can learn from each patient's unique movements over time may enhance the personalization and effectiveness of AI-driven physical therapy.

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REFERENCES

[1] A. Author and B. Author, "A review of physical therapy approaches in rehabilitation," *Journal of Rehabilitation*, vol. 25, no. 3, pp. 123–134, 2020.

[2] C. Author and D. Author, "Real-time human pose estimation: A survey," *Electronics*, vol. 13, no. 3, p. 1782, 2020.

[3] Z. Cao, T. Simon, S.-E. Wei, and Y. Sheikh, "Openpose: Realtime multi- person 2d pose estimation using part affinity fields," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 41, pp. 172–186, 2019.

[4] V. Bazarevsky, Y. Kartynnik, A. Vakunov, K. Raveendran, and M. Grundmann, "Real-time 3d hand pose estimation on mobile devices," *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pp. 1184–1194, 2020.

[5] M. Liu and L. Zhang, "Evaluating the accuracy of ai models for posture assessment in rehabilitation settings," *Journal of AI Research in Healthcare*, vol. 5, pp. 201–215, 2022.

[6] J. Anderson and R. Patel, "Ai in clinical rehabilitation: Challenges and opportunities," *Clinical Rehabilitation Journal*, vol. 29, pp. 78–85, 2021.

[7] A. Robinson and W. Chen, "Heatmap-based pose estimation for im- proved accuracy in therapeutic applications," *Computer Vision in Health- care*, vol. 14, pp. 150–160, 2020.
[8] M. Lopez and N. Green, "Real-time feedback mechanisms in pose estimation: A review," *Healthcare AI Journal*, vol. 11, pp. 92–101, 2021.
[9] Z. Cao, T. Simon, S.-E. Wei, and Y. Sheikh, "Realtime multi-person 2d pose estimation using part affinity fields," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 7291– 7299.
[10] M. Groos, F. Michel, A. Weikert, M. Bu¨scher, C. Sprunk, and S. Behnke, "Efficientpose: Scalable and efficient learning for 6d object pose esti- mation in rgb images," in *2020 International Conference on 3D Vision (3DV)*. IEEE, 2020, pp. 654–662.
[11] J. Redmon and A. Farhadi, "Yolov3: An incremental improvement," *arXiv preprint arXiv:1804.02767*, 2018.
[12] V. Bazarevsky, Y. Kartynnik, A. Vakunov, G. Riegler, M. Grundmann, and C. Sminchisescu, "Blazepose: On-device real-time body pose track- ing," *arXiv preprint arXiv:2006.10204*, 2020.
[13] K. Sun, B. Xiao, D. Liu, and J. Wang, "Deep high-resolution repre- sentation learning for human pose estimation," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2019, pp. 5693–5703.
[14] H.-S. Fang, S. Xie, Y.-W. Tai, and C. Lu, "Rmpe: Regional multi-person pose estimation," in *Proceedings of the IEEE International Conference on Computer Vision*, 2017, pp. 2334–2343.
[15] E. Insafutdinov, L. Pishchulin, B. Andres, M. Andriluka, and B. Schiele, "Arttrack: Articulated multi-person tracking in the wild," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 1293–1301.
[16] A. Mathis, P. Mamidanna, K. M. Cury, T. Abe, V. N. Murthy, M. W. Mathis, and M. Bethge, "Deeplabcut: markerless pose estimation of user- defined body parts with deep learning," *Nature Neuroscience*, vol. 21, no. 9, pp. 1281–1289, 2018.
[17] D. Mehta, H. Rhodin, D. Casas, P. Fua, H.-P. Seidel, and C. Theobalt, "Vnect: Real-time 3d human pose estimation with a single rgb camera," in *ACM Transactions on Graphics (TOG)*, vol. 36, no. 4, 2017, pp. 44–1.
[18] Mehta, H. Xu, O. Sotnychenko, F. Mueller, H. Rhodin, H.-P. Seidel, G. Pons-Moll, and C. Theobalt, "Holopose: Holistic 3d human reconstruction in-the-wild," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, 2020.
[19] G. Rogez, P. Weinzaepfel, and C. Schmid, "Lcr-net: Localization- classification-regression for human pose," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 3433– 3441.
[20] R. A. Gu¨ler, N. Neverova, and I. Kokkinos, "Densepose: Dense human pose estimation in the wild," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 7297–7306.