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Pose-based Hand Movement Tracking for Monitoring Psoriatic Arthritis Progression

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Abstract **-** Psoriatic arthritis (PsA) is a chronic inflammatory disease characterized by joint pain, stiffness, and reduced mobility, significantly impacting patients' quality of life. Accurate and continuous monitoring of hand mobility is crucial for assessing disease progression and therapy effectiveness. Traditional assessment methods often rely on subjective patient reports or sporadic clinical evaluations, leading to potential gaps in data and delayed therapeutic adjustments. This paper introduces a pose-based method for early detection and monitoring of psoriatic arthritis by analyzing hand closure movement videos recorded on smartphones. The proposed framework utilizes the Google *MediaPipe Hand* model to extract 3D hand joint coordinates from video sequences, which are then used to compute closing and stretching scores of the hand. These scores are derived using distance-based and angle-based metrics to quantify finger mobility, with a dedicated quality control mechanism ensuring that only videos meeting specific orientation and frame criteria are analyzed. Datasets comprising psoriasis patients and healthy individuals reveal that while the closing score offers robust and normalized measurements independent of anatomical variability, the stretching score requires lateral-view recordings for improved sensitivity. The results underscore the potential of this non-invasive, real-time tool to aid in early clinical intervention and long-term disease management. Future work will focus on integrating lateral-view analysis and joint thickness measurements for enhanced diagnostic accuracy.

Keywords**:** Psoriatic Arthritis, Hand Pose Estimation, Fist Closure Analysis, AI-Based Diagnosis, Smartphone Video Monitoring

1 INTRODUCTION

Psoriasis is a chronic inflammatory skin disease that affects approximately 2-3% of adults in Western populations, with an estimated 2 million affected individuals in Germany alone [1] [2]. While psoriasis primarily affects the skin, up to 30% of patients also develop psoriasis arthritis (PsA) [3], which affects not only the skin regions but also the joints, significantly impacting the quality of life [1] [4]. A significant challenge in managing psoriasis arthritis is the delay in diagnosis. Many patients experience arthritis symptoms several years before being diagnosed with PsA [3]. *Zabotti et al.* found that 58.9% of patients reported inflammatory symptoms in the months immediately prior to PsA diagnosis [5]. Given the potential for PsA to result in significant joint damage in its later stages, if such damage could be prevented with appropriate treatment, early detection and diagnosis are of the utmost importance [6]. The symptoms associated with psoriatic arthritis often accompany joint inflammation and functional impairment in the patient's hands [5]. Krueger *et al.* pointed out that about 66% of psoriatic arthritis patients have difficulty using their hands [7]. This finding is particularly pertinent to the present analysis. PsA is a condition that manifests in periods of rapid deterioration, known as flare-ups [1]. The objective of this study is to utilize the uploaded videos of hand-closure movements by patients to analyze the mobility of their fingers using pose estimation models. This approach has the potential to serve as an accessible tool for the early detection of disease deterioration, thereby enhancing the overall management of PsA.

2 RELATED WORK

Recent advancements in pose estimation models have paved the way for the development of novel medical applications. Simple smartphone recordings can be used to monitor human development, optimize performance, prevent injuries, and track motor progression in individuals with neurologic diseases [8]. During the COVID-19 pandemic, eHealth applications played a crucial role in patient communication and disease monitoring for individuals with chronic conditions, demonstrating promising results [9]. Telemedicine allows patients to make regular remote health status updates, which can be used to respond rapidly to illness exacerbation [10]. Pose estimation is another tool that can be integrated into smartphone applications for disease monitoring. For example, it has been applied to predict osteoarthritis by analyzing sit-to-stand videos [11] and to track knee kinematics in individuals with a history of stroke, aiding in rehabilitation monitoring [12]. Additionally, studies on Parkinson's disease have demonstrated the potential of hand movement tracking to diagnose and monitor musculoskeletal and neurological disorders. *Butt et al.* utilized RGB-D data to analyze tremors and bradykinesia, thereby providing quantitative assessments of motor function [13]. *Phatak et al.* employed convolutional neural networks (CNNs) on standardized smartphone photographs from arthritis patients to detect inflammation in three hand joints. They used the *MediaPipe* hand pose estimation technique to identify the relevant joints of the middle and index fingers, as well as the wrist joints, within the image [14]. For Psoriatic Arthritis (PsA), the Psoriasis Area and Severity Index (PASI) score is the highest validated score for quantitative evaluation of the clinical severity of psoriasis [15]. It evaluates both the extent of affected areas across the body and their level of severity. However, these approaches to monitoring disease progression rely on specialized hardware and often require medical personnel, limiting their applicability in nonclinical real-world settings.

2.1 Handpose Estimation Models

A multitude of models exist that possess the capability to estimate hand poses and determine the coordinates of hand joints within a specified frame. For instance, *OpenPose* [16] is a real-time multiperson 2D pose detection system, including body, foot, hand, and facial keypoints based on part affinity fields. Another robust model, *V2V-PoseNet* [17], offers highly precise 3D hand pose estimation by incorporating RGB image data and depth information. However, while being a very precise model, *V2V-PoseNet* is not very practical for our use case, as it requires RGB-D cameras, whereas we use smartphone recordings. *OpenPose*, on the other hand, only estimates 2D coordinates. Google's open-source *MediaPipe Hand* framework [18] [19] [20], with a focus on mobile deployment, provides an efficient alternative. A notable advantage of the *MediaPipe Hand Tracking* model (GMH) is its capacity to estimate a z-coordinate while maintaining a lightweight design, enabling its use in real-time applications on mobile devices. The joint points of the hand are determined for each video frame and subsequently made available as 3D coordinates. The GMH model is comprised of two subtasks. Initially, a palm detection sub-task is initiated, which endeavors to ascertain the position of the palm and delineate a bounding box around it. Subsequent to this, a hand landmark model is engaged, operating on the provided bounding box to generate 2.5D landmarks [18]. The model was trained with over 6,000 images from an in-the-wild dataset, an in-house collected dataset consisting of various hand gestures (10,000 images), and 100,000 images extracted from video data [18]. The GMH model demonstrates considerable promise in terms of its accuracy, particularly regarding its minimal hardware requirements, exhibiting an average precision of 95.7% [18]. By assessing dynamic exercises, such as the Hand Opening-Closure movement, the *MediaPipe Hand Tracking* model exhibits high temporal and spectral consistency with the gold standard [21]. The GMH model has the potential to be used in clinical applications, having a particularly high accuracy in tracking open-closure movements of the hand. Further adjustments, like adding a depth camera to the GMH model, can even further improve the model's effectiveness for clinical applications [21].

3 METHODOLOGY

The methodology employed in this research involves the analysis of a video recording of a fist closure, which is defined as the repetitive opening and closing of the hand. We extract the joint points of the hand from these video recordings using the GMH model [19]. Given the utilization of patient videos of domestic origin, characterized by non-standardized video inputs and the potential for suboptimal quality, alternative, more resource-intensive models might not be feasible. In addition to its low hardware requirements, GMH's z-coordinate estimation is crucial for measuring precise joint movements, such as calculating angles. GMH's ease of implementation renders it an accessible and practical choice for our application, thus making it the model of choice for our objective. The coordinates of all joint points for each video frame are extracted and serve as the fundamental data for subsequent calculations. These calculations include determining the velocity and uniformity of the hand closure, measuring the angles of the distal interphalangeal (DIP), proximal interphalangeal (PIP), and metacarpophalangeal (MCP) joints, and calculating various distances, including the distance from the fingertips (TIP) to the wrist. Analyzing these parameters facilitates the estimation of the extension trajectory of the fingers and provides insights into the overall mobility of the patient's hand.

A suitable video for the analysis is selected based on predefined quality criteria. Once the analysis is complete, the following data are saved: the coordinates of all landmarks for each frame; the angles of the DIP, PIP, and MCP joints for each frame; and the distance of the TIP to the wrist for each frame, which allows the course of movement to be tracked by plotting these distances. Based on these measurements the closing and stretching scores are computed. To execute our analysis, it is imperative to ascertain that the video, particularly the hand position, is commensurate with our calculations. Two hand positions are distinguished: the frontal view, necessary for the closing score, and the lateral view, essential for the stretching score, as shown in Figure 1.

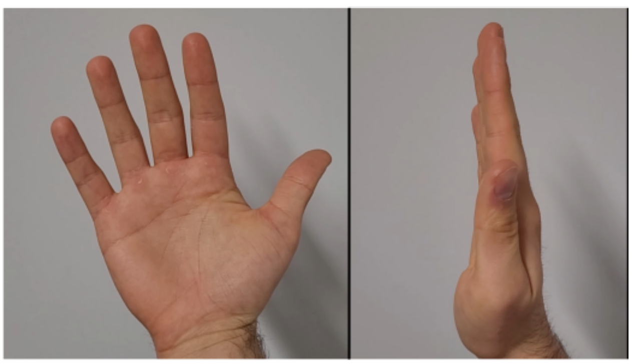

Fig. 1: Hand positions: frontal view (left) and lateral view (right)

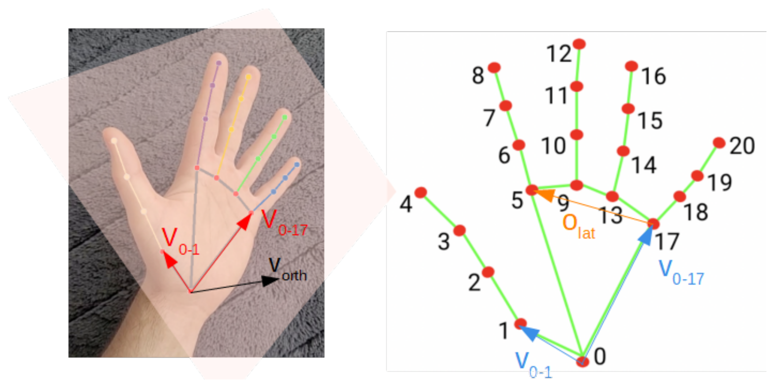

Fig. 2: The vectors v_{0-1} and v_{0-17} span the plane, v_{orth} is perpendicular to the plane and describes the orientation of the hand

3.1 Quality Criteria

For both hand positions, a set of requirements has been established to determine the hand's orientation and assess the video's overall suitability. In order to ensure a reliable evaluation, the video must fulfill several essential criteria. Primarily, the hand must be clearly visible throughout the entire sequence. Furthermore, the video should contain a minimum of 60 frames to guarantee sufficient data for analysis. Moreover, a minimum of three hand closures must be performed during the recording. Finally, and most importantly, the hand orientation must be consistent, either frontal, when calculating scores of closures, or lateral, when calculating scores of stretches. A series of additional criteria has been formulated to ensure a robust and precise assessment of hand orientation. For the frontal view, two specific vectors located on the ball of the hand define a plane. The vector perpendicular to this plane, denoted as v_{orth}, describes the frontal orientation of the hand relative to the camera. The methodology is illustrated in Figure 2, where the vectors v_{0-1} and v_{0-17} span the plane, and v_{orth} is shown as perpendicular to it. It is important to note that this plane is regarded as an approximation of an optimally stretched hand, proving useful when determining its stretching capability.

For the lateral view, the vector o_{lat} was selected, defined by the passage through the landmarks 5 and 17. This vector facilitates accurately determining the lateral orientation, which is critical when the hand does not face the camera directly. In addition to orientation analysis, our framework incorporates a palm recognition mechanism to differentiate between the palm and the back of the hand. This is achieved by computing the cross product of the vectors v_{0-1} and v_{0-17}; a sign change in the cross product indicates a hand rotation, thereby enabling a reliable determination of palm versus back-of-hand presentation.

Furthermore, detecting a fist is based on a precise geometric configuration. Specifically, a finger is considered “closed” when the distal phalanges are positioned closer to the carpometacarpal joints (CMCs) than the MCPs. When this configuration is observed in all digits, the hand is classified as being in a closed or fist state.

In addition to these defined criteria, an overall quality metric provided by *MediaPipe*, termed as the general frame score, is incorporated into our analysis. This score reflects the efficacy with which the joint points are detected and is particularly sensitive to the visibility of the hand. A low general frame score typically indicates that the hand is not clearly delineated within the frame, making it unsuitable for our analysis.

Integrating these criteria into our evaluation framework not only enhances the reliability of the hand orientation measurements but also ensures that subsequent analyses are based on high-quality and unambiguous input data. The following Table 1 shows the criteria employed for the frontal and lateral views.

Table 1: Criteria for determining the frontal and lateral view of the hand

Criteria	Frontal View	Lateral View
frontal orientation	> 0.85	< 0.5
lateral orientation	✗	> 0.70
palm detection	✓	✗
general frame score	> 0.85	> 0.65

4 STRETCHING AND CLOSING CAPABILITIES OF THE HAND

4.1 Stretching Score Calculation

Two distinct methodologies are employed to ascertain the stretching score, which describes the opening capabilities of the hand.

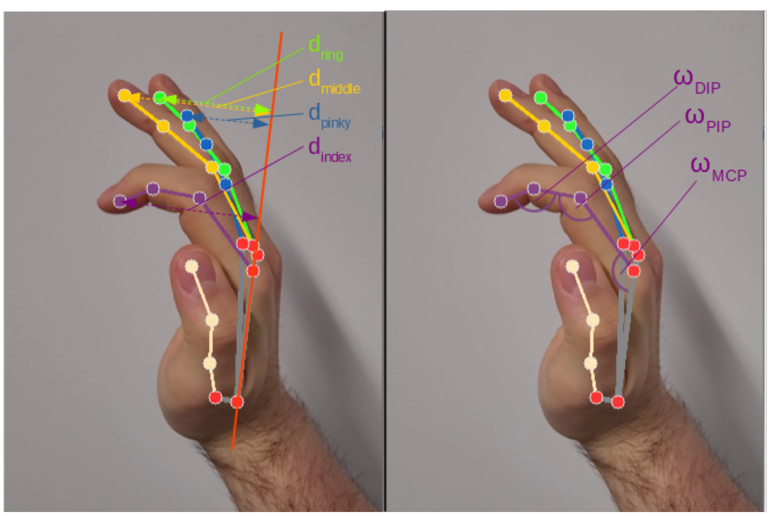

Fig. 3: Determining the stretching score with the TIP to plane distance (left) and the angles (right)

Distance-based method: To assess the stretching capability of the hand, the distance *d* from the fingertips to the plane, as shown in Figure 3, is calculated for all TIP joint points. The smaller this distance, the higher the score for the extension. Furthermore, for each finger identified as closed, the stretching score for that finger is set to 0. This is significant because the distance decreases in fully stretched and closed positions. The extension is deemed optimal (score = 1) if a joint point falls below the predefined threshold t_1. Conversely, if it exceeds the threshold t_2 (or if the finger is found to be closed), the score is 0. These thresholds, t_1 and t_2, are determined empirically for each finger.

Angle-based method: A second method of determining the stretching capability is to look at the angles ω of the DIP, PIP, and MCP joints, as depicted in Figure 3. These can be computed by looking at the adjacent landmarks. An angle ω close to 180° means it's fully stretched, and an angle ω between 0° and 90° can be seen as fully closed. Similar to the distance-based method, the maximal angles are determined and mapped to a score between 0 and 1. The final stretching score is obtained by taking a weighted average of the three angle scores, with slightly more importance given to the scores of ω_{MCP} and ω_{PIP}.

4.2 Closing Score Calculation

Analogous to the initial distance-based stretching score method, a closing score can be determined by tracking the distance from the fingertips to the wrist. This score serves as an indicator of the hand's closing capabilities. As with the stretching score, smaller distances indicate higher scores, and thresholds are employed once more to map the actual distance to a closing score. If a finger is not recognized as closed, the score for that finger is designated as 0. In the context of absolute distances in the frontal view, the depth of the hand exerts a substantial and undesirable influence. To ensure the independence of distances from the z-coordinate, a division of the actual distance-value by the sum of the vectors v_{0-5} and v_{0-17} is necessary. This results in a more stable relative distance. By plotting the scaled TIP-to-wrist distance for each frame and finger, as shown in Figure 4, we get a useful graph for tracking the movement of the hand when opening and closing.

Additionally, we apply peak detection to find the minimum distance to the wrist and calculate the average of the minima to get a more stable value. This mean distance is then employed as the metric for assessing the closing score of a video. Furthermore, we can use the peak points to determine the number of hand closures performed in a video.

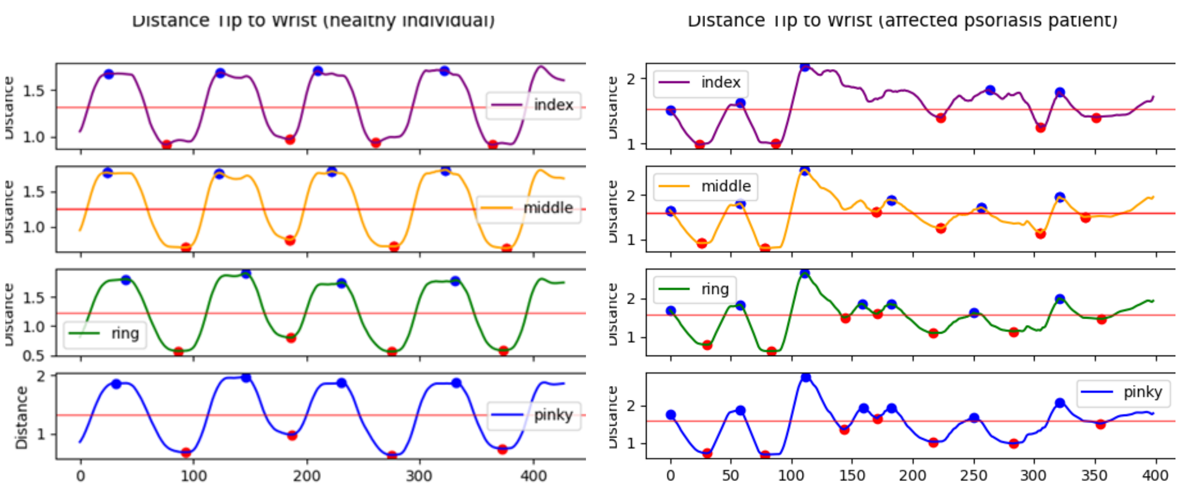

Fig. 4: TIP-to-wrist distance plotted with peak detection for each frame and finger of a healthy patient (left) and an affected patient (right)

5 EXPERIMENTS

To evaluate the developed methods, we conducted experiments using two distinct datasets. The first dataset comprised video recordings from 35 psoriasis patients, resulting in approximately 400 videos. The number of videos per patient series varied significantly, ranging from 1 to 92 videos per series. All patient videos were recorded from a frontal view, which poses a challenge when applying the developed stretching score methods, as these methods are specifically designed for lateral view recordings. Additionally, we analyzed an in-house dataset containing approximately 120 video recordings of healthy individuals recorded under standardized conditions from frontal and lateral perspectives.

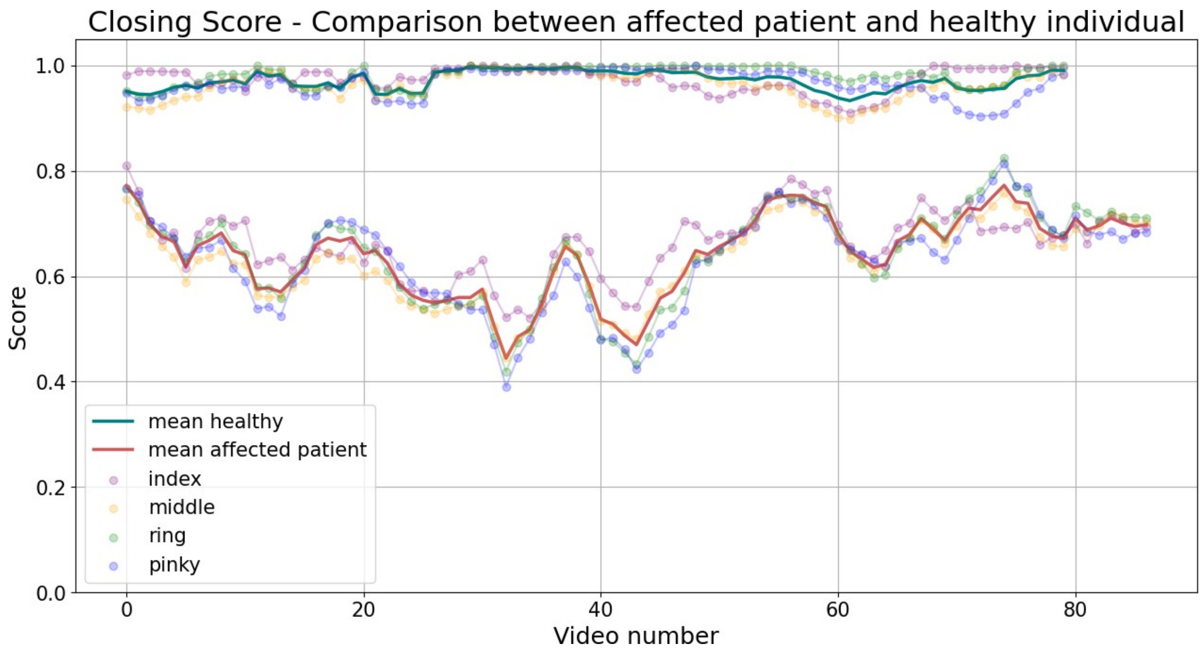

Fig. 5: Comparison of the closing score of an affected and a healthy patient for each finger over a period of 17 months

Figure 5 illustrates the closing score over a sequence of 85 video recordings, comparing the fist-closing performance of a psoriasis-affected patient with that of a healthy individual. The closing score, ranging from 0 (no closure) to 1 (complete closure), quantifies the ability of each finger to perform the closing motion. The plot displays the average closing score of all fingers for both the healthy subject (cyan curve) and the affected patient (red curve), alongside individual finger scores—index (purple), middle (orange), ring (green), and pinky (blue). The healthy subject demonstrates consistently high closing scores, with minimal variation across videos, indicating stable and complete finger closure. In contrast, the affected patient's finger scores exhibit significant fluctuations and generally lower values, particularly noticeable in the middle segment of the video sequence (video numbers ~20–60), suggesting impaired and variable motor performance. Notably, the pinky and ring fingers show the most significant deviation from the healthy baseline, highlighting potential finger-specific functional limitations due to the disease. The mean closing score for the patient remains consistently below that of the healthy individual, validating the score's sensitivity in capturing motor impairments associated with psoriasis.

5.1 Stretching Score Extraction from Frontal View Recordings

Since the developed stretching score methods require lateral view recordings, an intuitive alternative for frontal view videos would be to measure the TIP-to-wrist distance. In contrast to the minimum distance utilized in calculating the closing score, the maximum distance would be used instead. However, this approach exhibits significant limitations. One major drawback is the inherent variability introduced by finger length differences, as individuals with longer fingers naturally achieve higher maximal values. This results in inconsistencies and complicates the establishment of a standardized stretching score. Additionally, the approach lacks sensitivity in the near-full-stretched range, where the TIP-to-wrist distance changes only minimally. Consequently, the frontal view method proves inadequate for precise stretching score determination. Given the limitations of the frontal view approach, we developed two alternative methods for calculating the stretching score, tailored explicitly for lateral view recordings. In contrast to the stretching score, the closing score is inherently bounded, as the minimal distance between the fingertip and wrist is consistently zero, regardless of finger length. This characteristic ensures consistent mapping and high sensitivity in the range close to full-finger flexion. Therefore, the closing score method is more suitable for accurately capturing extension variations.

6 DISCUSSION

The experimental results indicate that the TIP-to-wrist approach in frontal view for calculating the stretching score is fundamentally flawed due to the variability introduced by finger length and the lack of sensitivity at near-full extension. These limitations became evident during the analysis of patient videos, where inconsistencies in scoring were prominent, particularly in individuals with longer fingers. This finding emphasizes the critical need for a lateral view setup to ensure reliable stretching score assessments. The introduction of the closing score method in frontal view demonstrates clear advantages over the stretching score method using the maximum TIP-to-wrist distance. Its inherent bounded nature allowed for consistent scoring irrespective of finger length, and the method's sensitivity in the critical range near full flexion made it highly effective for precise mobility assessments. Furthermore, the visual analysis of extension progression confirmed that healthy individuals displayed smooth, continuous curves, while psoriasis patients exhibited irregular patterns indicative of impaired mobility, as shown in Figure 4. The robustness of the closing score method was further demonstrated through longitudinal tracking, as shown in Figure 5, where the progression of finger mobility over a 17-month period was clearly observable. Applying a moving average filter improved data interpretation, highlighting gradual changes over time. These findings validate the suitability of the closing score method for long-term monitoring and comparative studies between affected and healthy individuals. In summary, the experimental results substantiate the effectiveness of the closing score method as a reliable alternative to the stretching score in the frontal view approach.

7 CONCLUSION & FUTURE WORK

This study aimed to monitor disease progression in psoriasis patients by analyzing homemade videos to track the overall flexibility in their fingers. To this end, we have developed methodologies to quantify each finger's closing and stretching capabilities. These methodologies have been instrumental in quantifying the numerical score values and generating diagrams that offer valuable insights into patients' extension capabilities. By plotting the scores across a video series, we obtained a meaningful way to track the patient's finger flexibility progression, which is an essential parameter because limited finger flexibility is strongly associated with the onset of psoriasis arthritis. This methodology can be utilized not only to monitor treatment progression but also to inform clinical decision-making. At present, our dataset of affected patients primarily consists of frontal-view recordings, which have proven suboptimal for the analysis of stretching capabilities. However, we have described two promising alternative methods that can be used in lateral-view recordings to more accurately determine a stretching score from hand-closure recordings. Extending our dataset with lateral-view recordings from psoriasis patients will facilitate further evaluation and improvement of the tracking capabilities of our methods. In the context of hand analysis for patients with PsA, another promising parameter that merits investigation is finger joint thickness. This is because joint swelling in the fingers is also one of the first indicators of a progression toward psoriasis arthritis [22] [6]. To further enhance our analysis, we aim to develop methods to measure joint thickness, as it can also be extracted from the video material we already have. Incorporating this additional parameter can facilitate the early detection of disease deterioration, thereby enhancing the efficacy of disease monitoring.

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