ExerAIde: AI-assisted Multimodal Diagnosis for Enhanced Sports Performance and Personalised Rehabilitation

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Abstract

The quest for personalized sports therapy has long been a concern for practitioners and patients alike, aiming for recovery protocols that transcend the one-size-fits-all approach. In this study, we introduce a novel framework for personalized sports therapy through automated joint movement analysis. By synthesizing the analytical capabilities of a Random Forest Classifier (RFC) with a Vector Quantized Variational AutoEncoder (VQ-VAE), we systematically discern the nuanced kinematic differences between healthy and pathological exercise movements. The RFC prioritizes the joints by their discriminative influence on movement healthiness, which informs the VQ-VAE's derivation of a distilled list of pivotal joints. This dual-model approach not only identifies a hierarchy of joint importance but also ascertains the minimal subset of joints critical for distinguishing between healthy and unhealthy movement patterns. The resultant data-driven insight into joint-specific dynamics underpins the development of targeted, individualized rehabilitation programs. Our results exhibit promising directions in sports therapy, showcasing the potential of machine learning in developing personalized therapeutic interventions.

1. Introduction

Personalized sports therapy represents a cutting-edge advancement in rehabilitative health care, promising personalised treatment plans that are tailored to meet the specific requirements of each person. This approach is grounded in the precise identification and strategic enhancement of particular physiological aspects that constrain an individual's athletic performance or recuperation process. In this study, we introduce a novel technique that leverages the capabilities of a Random Forest Classifier (RFC) [2] and Vector Quantized Variational Autoencoder (VQ-VAE) [20] to herald new prospects in personalised sports therapy. With machine learning's rise to prominence, its applicability in health-related fields has become increasingly evident, offering enhanced analytical proficiency to unravel complex biological data [10, 14, 15, 21]. Our investigation employs this to dissect the subtleties of joint movements during physical activity. By employing RFC and VQ-VAE model as our primary analytical tools, we distill high-dimensional motion data into detailed embeddings that reveal the joint movement disparities between healthy and unhealthy individuals. Our research involves the IntelliRehab Dataset (IRDS) [16] in which participants, equipped with advanced motion-capturing sensors, performed a variety of exercises. Our framework is utilized to generate detailed embeddings of these movements, which enabled us to pinpoint specific joints where movements in unhealthy subjects deviated from those observed in healthy counterparts. From these insights, we propose a tailored exercise program designed to strengthen the identified problematic joints. The essence of our approach is customized therapy to meet the biomechanical needs of each patient, promoting a directed and effective rehabilitation strategy.

Proper form and technique are essential for optimal performance and injury prevention in sports and physical therapy [19]. However, monitoring and evaluating exercise form and body mechanics can be challenging, particularly in remote or unsupervised settings. Traditional methods often rely on human experts or specialized equipment, which can be time-consuming, costly, and limited in scalability. Recent advancements in computer vision and deep learning techniques have opened up new possibilities for automated analysis of human motion and body mechanics [1]. The proposed approach in our study utilizes a two-stage process. First, RFC predicts the top priority joints based on the specific exercise or movement. Subsequently, a VQ-VAE based representational technique takes key-point estimation and depth maps data of individuals in images as input, focusing on the top priority joints identified by the RFC. This technique aims to parse and assess (im)proper form for various sports-specific movements and exercises used in physical therapy, providing a valuable tool for performance enhancement, injury prevention, and rehabilitation monitoring.

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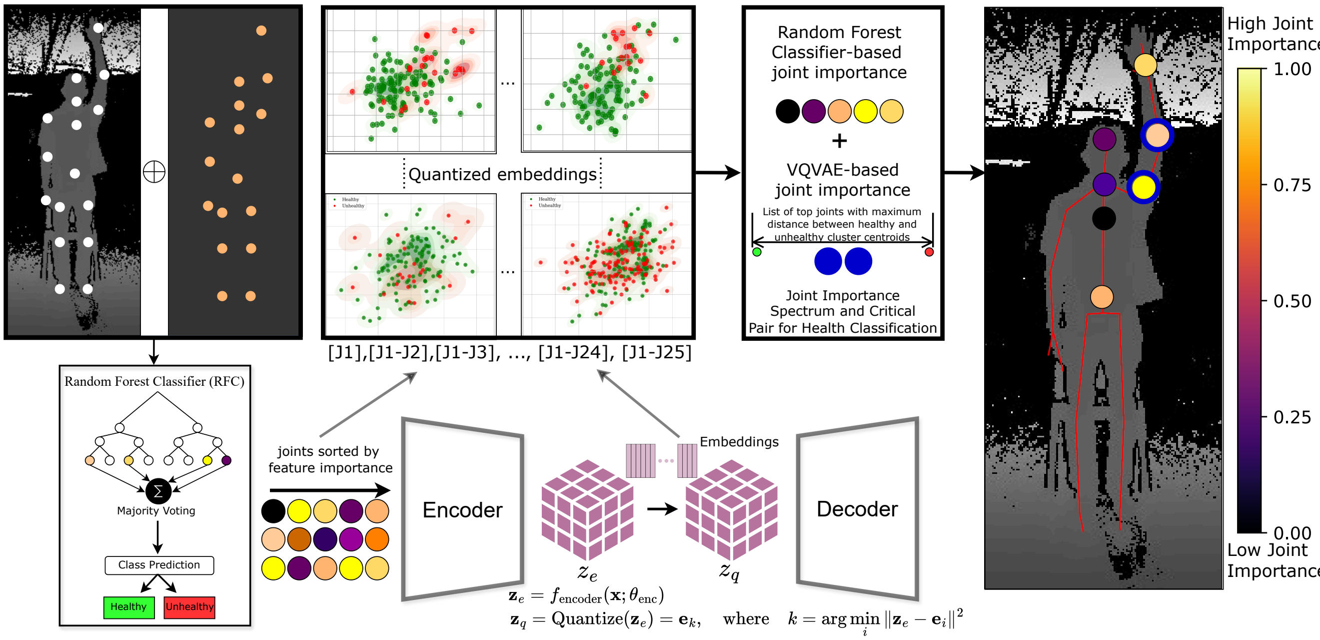

Figure 1. Illustration of the integrated approach used to identify key joints in differentiating healthy from unhealthy subjects based on their movement patterns. The process begins with the collection of depth map pixels and corresponding joint keypoints. This data is fed into a VQ-VAE, which compresses the information into a quantized latent space representation through its encoder and decoder architecture. Concurrently, a Random Forest Classifier (RFC) assesses the significance of each joint in classifying movements as healthy or unhealthy by analyzing the keypoints and employing majority voting for class prediction. The outcome is a ranked list of joints by feature importance as determined by RFC, with the VQVAE-based analysis further highlighting the joints with maximum centroid distance between healthy and unhealthy clusters, depicted in the scatter plot. The resulting visualization provides a clear depiction of joint importance, with a gradient scale reflecting the significance from low (purple) to high (yellow), and marks the joints with the highest discriminative power using blue circles, bridging the gap between latent space embeddings and clinical interpretability.

2. Related work

A growing area of research within sports therapy has been the personalized rehabilitation for individuals with movement impairments, including those suffering from chronic diseases. Nonnekes et al. [17] emphasized the necessity for individualized non-pharmacological interventions in the management of gait impairments in Parkinson's patients, calling for a tailored approach that accounts for patient-specific characteristics to predict the efficacy of various training modes. Similarly, Zeng et al. [22] explored the intersection of artificial intelligence (AI) and health management, specifically in the context of long-term sports rehabilitation. Their study, which applied AI to assess sports rehabilitation outcomes, supports the integration of machine learning for personalized health services, highlighting the potential benefits of AI in promoting national fitness and health. Kempitiya et al. [8] focused on leveraging AI and Virtual Reality (VR) to deliver personalized physiotherapy rehabilitation. Their work is pioneering the integration of AI with single-player VR gaming to customize physiotherapy for patients with diverse needs, potentially revolutionizing patient-centered care in physiotherapy. Moreover, Lidströmer et al. [11] presented an overview of how AI can be incorporated into physiotherapy and rehabilitation. Their work discusses various AI applications that could enhance the supportive frameworks of physiotherapy, such as real-time video instructions and pose detection for optimal feedback, thus making physiotherapy more personalized and accessible. Furthermore, datasets like NTU RGB+D 120, have become benchmarks for 3D human activity understanding. It includes RGB and depth videos capturing diverse activities. The dataset facilitates algorithm evaluation and advances research in human activity recognition [13]. Recent advancements by Deyzel and Theart [5] in one-shot skeleton-based action recognition further the potential for intelligent virtual coaching in sports rehabilitation, demonstrating the efficacy of graph convolutional networks in classifying strength and conditioning exercises from limited samples.

These studies lay the foundation for the present research, which builds upon the premise of using advanced machine learning techniques to facilitate personalized sports therapy regimens based on the analysis of kinematic joint movement data. Unlike prior approaches that often require extensive labeled datasets, our method capitalizes on the RFC's feature importance to determine key joints and utilizes VQ-VAE's robust embedding capabilities to identify the minimal essential joints that differentiate healthy from pathological movement patterns. This approach embodies the novelty of our work, as it enables the distillation of complex biomechanical data into actionable insights, resulting in rehabilitation strategies that are both personalized and automated.

3. Methods

In the study, we employed a two-step analysis to investigate the significance of specific joints in differentiating between healthy and unhealthy subjects during exercise. Initially, we trained a VQ-VAE on 4D skeleton keypoint data, allowing the model to learn a latent representation of the dataset. Subsequent to this, RFC was utilized to ascertain the importance of each joint. Leveraging the joint importance rankings provided by the RFC, we conducted a systematic evaluation by progressively reducing the number of joints considered, starting with the top 25 and decrementing down to a single joint. For each subset, we computed the quantized embeddings using the VQ-VAE and calculated the centroid distance between the healthy and unhealthy clusters. **Figure 1** illustrates our methodology.

3.1. VQ-VAE

The VQ-VAE model training involves mapping the input data $\mathbf{x}$ into a latent embedding space $\mathbf{z}_e$ through an encoder function, followed by quantizing $\mathbf{z}_e$ to obtain a discrete latent representation $\mathbf{z}_q$. The quantized vector $\mathbf{z}_q$ is then utilized to reconstruct the input data through a decoder. This process introduces a vector quantization operation that enables learning discrete latent representations.

3.1.1 VQ-VAE architecture

The VQ-VAE architecture comprises three primary components: the encoder, the vector quantization layer, and the decoder.

- **Encoder:** The encoder maps the input data $\mathbf{x}$ to a continuous latent embedding space $\mathbf{z}_e$, formulated as $\mathbf{z}_e = f_{\text{encoder}}(\mathbf{x}; \theta_{\text{enc}})$, where θ_{enc} denotes the encoder parameters.
- **Vector Quantization Layer:** The continuous latent embeddings $\mathbf{z}_e$ are quantized to $\mathbf{z}_q$ by finding the nearest vector $\mathbf{e}_i$ from a predefined set of embeddings $\mathbf{E} = \{\mathbf{e}_i\}$:

$$\mathbf{z}_q = \text{Quantize}(\mathbf{z}_e) = \mathbf{e}_k, \quad \text{where} \quad k = \arg\min_i \|\mathbf{z}_e - \mathbf{e}_i\|^2$$

- **Decoder:** The quantized embeddings $\mathbf{z}_q$ are used to reconstruct the input data $\hat{\mathbf{x}} = f_{\text{decoder}}(\mathbf{z}_q; \theta_{\text{dec}})$, where θ_{dec} represents the decoder parameters.

3.1.2 Loss function

The VQ-VAE model's training objective combines the reconstruction loss with a quantization loss to ensure effective learning of the discrete latent representations:

- The reconstruction loss, typically the mean squared error (MSE) for continuous data, is given by:

$$\mathcal{L}_{\text{recon}} = \|\mathbf{x} - \hat{\mathbf{x}}\|^2$$

- The quantization loss penalizes the distance between $\mathbf{z}_e$ and $\mathbf{z}_q$, encouraging accurate quantization:

$$\mathcal{L}_{\text{quant}} = \|\text{sg}[\mathbf{z}_e] - \mathbf{z}_q\|^2 + \beta\|\mathbf{z}_e - \text{sg}[\mathbf{z}_q]\|^2$$

  where sg denotes the stop-gradient operator, and β is a hyperparameter.

The overall loss function combines these two losses:

$$\mathcal{L} = \mathcal{L}_{\text{recon}} + \mathcal{L}_{\text{quant}}$$

Optimizing this objective function allows the VQ-VAE to encode input data into discrete latent representations, capturing the key features of the data and enabling various applications such as data generation and manipulation in the latent space.

3.1.3 VQ-VAE training details

The model is trained using the Adam optimizer [9] with a learning rate of 1×10^{-3} for 1000 epochs, adjusting for convergence.

3.2. Random Forest Classifier (RFC)

The RFC, an ensemble learning method, functions by constructing numerous decision trees during training and outputting the class that is the mode of the classes (classification) of the individual trees. Mathematically, for a decision tree $h(\mathbf{x}, \Theta_k)$, with $\mathbf{x}$ representing the input features and Θ_k the randomness in the k^{th} tree, it is defined as:

$$H(\mathbf{x}) = \frac{1}{K}\sum_{k=1}^{K} h(\mathbf{x}, \Theta_k) \tag{1}$$

where K denotes the total number of trees.

RFC is employed to analyze the joint data, treating each joint as a feature in differentiating between healthy and unhealthy movement patterns.

3.2.1 RFC training and hyperparameter details

The configuration of the RFC is set with $n\_estimators = 250$ and $random\_state = 42$, where $n\_estimators$ indicates the number of trees in the forest, and $random\_state$ ensures the reproducibility of the results. This configuration is selected based on a parameter sweep that

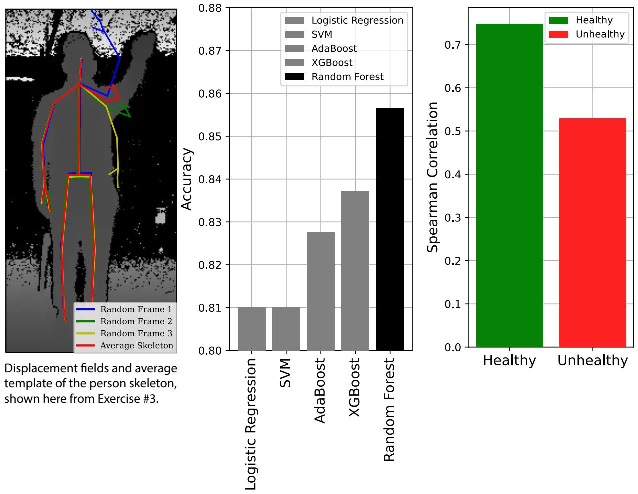

Figure 2. **Left)** Visualization of skeletal motion during Exercise 3, captured at three distinct time frames. The colored skeletons represent the joint positions at each frame, with the average skeleton plotted in red for reference. The difference between skeletal motion and the colored skeleton represents the displacement fields. **Mid)** Comparative accuracies of different classifiers with RFC outperforming SVM, AdaBoost, XGBoost, and Logistic Regression. **Right)** Spearman correlation comparison, depicting the strong alignment of our framework's joint importance ranking with the ground truth displacement fields, substantiating the efficacy of our method in distinguishing between healthy and unhealthy movement patterns.

assessed the model's performance for $n\_estimators$ in $\{75, 100, 250, 500, 1000\}$. The choice of 250 trees was determined as optimal, balancing model complexity, computational efficiency, and classification accuracy.

3.3. Sports therapy dataset

The dataset for this study is derived from the IntelliRehabDS (IRDS) [16], a rich repository of kinematic data designed to support the analysis of physical rehabilitation exercises. Captured through the Kinect motion sensor camera, the IRDS dataset encompasses a detailed record of various rehabilitation movements, meticulously performed by a cohort of 29 individuals, inclusive of both patients (unhealthy subjects) and healthy controls. A notable feature of this dataset is its detailed capture of the 3D coordinates of 25 body joints for each participant, coupled with the corresponding depth maps for every recorded frame. Moreover, it furnishes essential annotations such as the type of gesture or exercise performed, the subject's position (either standing or sitting), and a correctness label to gauge the accuracy of the movements.

The focused subset of the IRDS dataset, pertinent to our analysis, consists of 2577 gesture sequences, all of which were tagged with correctness labels of 1 (healthy) or 2 (unhealthy), indicating a binary assessment of the exercise performance (correct or incorrect) rather than a discrete measurement of correctness levels. Among these, 1215 gestures were executed in a standing position, 952 in a seated position on a chair, 359 while seated on a wheelchair, and 51 with the support of a stand frame. **Table 1** provides the description of each exercise performed by the subjects in the dataset.

Idx.	Exercise Name	Description
1	Elbow Flexion Left	Flexion and extension movement of the left elbow joint
2	Elbow Flexion Right	Flexion and extension movement of the right elbow joint
3	Shoulder Flexion Left	Flexion and extension movement of left shoulder while keeping the arm straight in front of the body
4	Shoulder Flexion Right	Flexion and extension movement of right shoulder while keeping the arm straight in front of the body
5	Shoulder Abduction Left	The left arm is raised away from the side of the body while keeping the arm straight
6	Shoulder Abduction Right	The right arm is raised away from the side of the body while keeping the arm straight
7	Shoulder Forward Elevation	With hands clapped together, the arms are kept straight and raised above the head, keeping the elbows straight
8	Side Tap Left	The left leg is moved to the left side and back while keeping the balance
9	Side Tap Right	The right leg is moved to the right side and back while maintaining balance

Table 1. Exercises' description in the IntelliRehabDS dataset [16].

For the purpose of this study, the dataset is segmented based on the subject's position during the exercise, effectively bifurcating it into two distinct groups: exercises performed while standing and those conducted while seated. This demarcation was motivated by the premise that the biomechanical dynamics and the muscular engagement differ significantly between standing and sitting postures [12, 18], which, in turn, could influence the efficacy of the rehabilitation exercises and their analysis.

3.3.1 4D key-points and depth features

The dataset is organized into a 4-dimensional format, where the input channels corresponded to the x, y, z coordinates and the pixel value of the depth at each joint location. This 4D data encapsulation augments the traditional 3D representation with the additional context of environmental interaction, providing a comprehensive portrayal of the subject's movements within their spatial milieu. The depth dimension presents several analytical advantages. Primarily, it enhances spatial awareness, contributing to a precise estimation of the joint positions. It addresses ambiguities inherent in 2D projections and 3D models, especially in scenarios of joint occlusion or overlap. Moreover, the depth information is robust to changes in camera perspective, ensuring consistent spatial relationship comprehension. This fourth dimension also offers contextual clues pivotal for the classification of movements, aiding in the discrimination between healthy and pathological motion patterns. In essence, the integration of depth as a fourth dimension is instrumental in fortifying the model's capacity to discern subtle kinematic discrepancies, which is paramount for the nuanced evaluation of physical rehabilitation exercises.

4. Results

4.1. RFC-based keypoints' priority

Our exploration into the significance of individual joints via RFC unveiled compelling insights. The RFC's findings highlight the key joints involved in an exercise that are instrumental in discriminating between healthy and pathological movement patterns. For instance, in *Exercise 1*, which primarily engages the left elbow joint, it is precisely the left arm's keypoints that emerge as crucial discriminators between the healthy and unhealthy cohorts. This pattern holds true across exercises; in *Exercise 9*, for example, the right leg and spine joints are critical for classification. These nuances of joint importance for each exercise are visually encapsulated in the second panel of the plots in **Figure 3**. Moreover, **Figure 4** provides a comprehensive portrayal of the range of movements for each exercise, along with an enumeration of joints based on their RFC-determined importance. Notably, this figure also delineates the most significant joints for each exercise in the lower right corner, offering a succinct reference for the joints that bear the highest discriminative power. Complementing our findings, the displacement field illustrations in **Figure 2** graphically represent the dynamic involvement of joints throughout the temporal sequence of *Exercise 3*. It is evident from the displacement fields that the left arm's joints are actively engaged — a conclusion that aligns with our RFC analysis, reaffirming its validity.

In our comparative analysis, RFC was selected due to its superior classification accuracy over alternative models such as Support Vector Machines (SVM) [4], AdaBoost [6], XGBoost [3], and Logistic Regression [7], as indicated by the results in **Figure 2**. These findings showcase RFC's effectiveness in handling complex datasets with multiple features and high dimensionality [2].

4.2. VQVAE-based muscle joints' prediction

The VQ-VAE analysis elucidated that only two joints, identified as paramount by the RFC, were indispensable for achieving the maximal centroid separation in the latent space between healthy and unhealthy movement patterns. This discernment accentuates the salience of specific joints in characterizing movement quality, which bears substantial implications for the formulation of targeted rehabilitation regimens. Concentrating on these pivotal joints within therapeutic exercises may potentiate rehabilitation efficacy and expedite convalescence. In our methodical exploration, we computed the centroid distances between the clusters of healthy and unhealthy joint movements, progressively decreasing the count of joints from twenty-five to a singular one. The Euclidean distance was employed as the distance metric, formalized as:

$$d(\mathbf{h}, \mathbf{u}) = \sqrt{\sum_{i=1}^{n} (h_i - u_i)^2}$$

where $\mathbf{h}$ and $\mathbf{u}$ represent the centroids of the quantized embeddings for the healthy and unhealthy configurations, respectively, within the n-dimensional latent space. The analysis incontrovertibly revealed that for each exercise, a duo of joints sufficed to unambiguously demarcate between the healthy and unhealthy classes. **Figure 3** visually encapsulates this phenomenon, delineating the quantized embeddings that exhibit the largest centroid distances. This visualization not only reaffirms the empirical findings but also enhances comprehension of the spatial dichotomy between divergent movement qualities. The precise delineation of these critical joints through RFC and VQ-VAE analyses significantly augments our understanding of human movement biomechanics, offering pivotal insights into the substratum of healthy versus compensatory motion patterns.

The final section of **Figure 2** illustrates the robustness of our model, revealing a high correlation with ground truth displacement fields derived from kinematic data. These fields were computed by assessing the deviation of each movement frame from the mean skeletal structure across a motion sequence. By ranking these displacements from highest to lowest and correlating them with our model's joint importance hierarchy through Spearman's method, we obtain values exceeding **0.7** for healthy and **0.5** for unhealthy subject movements. This suggests our model's proficiency in differentiating between varying movement qualities, a critical factor for customizing therapeutic measures in sports medicine. The congruence between high displacement joints in raw data and the joints our framework identifies confirms the potential for more nuanced, targeted rehabilitation strategies.

4.3. Automated sports therapy

Our results demonstrate the effectiveness of the proposed two-stage approach in parsing proper and improper form for sports-specific movements and physical therapy exercises. By first identifying the top priority joints using the RFC and then leveraging the VQ-VAE representational technique on key-point estimation data and depth maps, the model can effectively capture and encode the most relevant information required for accurate analysis of body mechanics. The model's ability to differentiate between proper and improper form is illustrated in **Figure 3**, representing nine different postures or exercise positions, labeled from 1 to

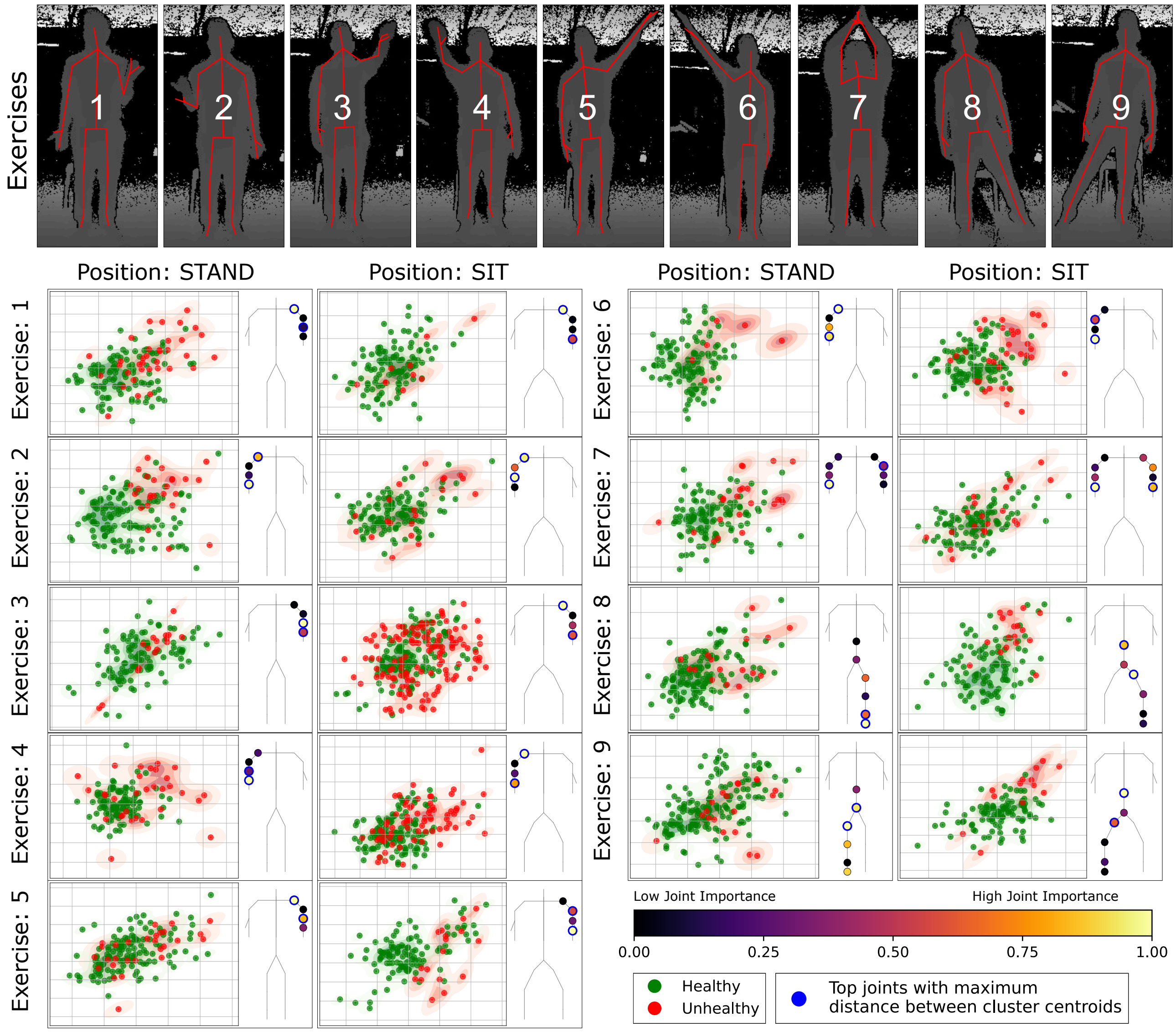

Figure 3. Comparative analysis of healthy and unhealthy subjects' movements across nine different exercises, performed in standing and sitting positions. The upper panel illustrates depth sensor images of a subject executing the exercises, with the exercise number superimposed. The lower panel presents the VQ-VAE-derived quantized latent space embeddings, where each scatter plot corresponds to the exercise above. Red and green dots represent unhealthy and healthy movements, respectively. Keypoints are colored according to their importance as determined by the RFC, following the inferno heatmap color scheme from low (dark purple) to high (bright yellow). The blue circles denote joints with the maximum distance between centroids of healthy and unhealthy clusters, highlighting their significant role in distinguishing movement quality. This visualization underscores the importance of specific joints in the assessment of movement patterns for rehabilitation purposes.

9. Each position is accompanied by a visual representation and a classification of whether it is a sitting (SIT) or standing (STAND) position. Additionally, the figure highlights the importance of specific joint positions by indicating their relative importance levels. Joints labeled as "High Joint Importance" are considered crucial for maintaining proper form and body mechanics, as determined by RFC for the specific exercise or movement. Joints labeled as "Low Joint Importance" have a lesser impact on the overall assessment.

Through the combination of RFC for joint prioritization and the VQ-VAE representational technique on keypoint estimation and depth maps, the proposed approach can effectively parse and assess the various sports-specific movements and physical therapy exercises. This capability holds significant potential for applications in remote training and rehabilitation monitoring, injury prevention, and performance optimization, enabling athletes, coaches, and physical therapists to receive real-time feedback and corrections on form and body mechanics, with a focus on the most critical joint positions/exercise or movement.

4.4. Discussion

Our combination of RFC-based keypoint importance and VQVAE-based joint analysis highlights the significance of tailoring rehabilitation exercises to the individual's specific needs, especially within the context of sports-related recoveries. This personalization is particularly crucial in addressing the precise biomechanical deficits and compensatory strategies that are often unique to each individual's pathology. For *Exercise 1*, involving the left elbow, the RFC identified the left arm's keypoints—*HandLeft*, *WristLeft*, *ShoulderLeft*, and *ElbowLeft*—as the most critical for discriminating healthy from unhealthy movements. In concordance, the VQVAE pinpointed *HandLeft* and *ShoulderLeft* as the two joints whose embeddings exhibited the greatest centroid distances, reaffirming their crucial role in the assessment and correction of elbow flexion exercises. This synergy in findings suggests a focus on these joints could enhance the efficacy of rehabilitation for conditions affecting elbow mobility. Similarly, in *Exercise 2*, the RFC highlighted the importance of the *WristRight* and associated joints, which was validated by the VQVAE's identification of the *WristRight* and *ShoulderRight* as key discriminators of movement quality. This insight is indicative of the necessity to concentrate on wrist dynamics in this particular exercise during rehabilitation, which may often be overlooked in favor of larger muscle groups.

The alignment between RFC and VQVAE findings was not limited to upper-body exercises. In *Exercise 8*, focusing on lower-body coordination, the *AnkleLeft* and *FootLeft* emerged as significant from both analyses, suggesting that attention to ankle-foot mechanics could be paramount in rehabilitation programs targeting balance and gait stability. The convergence of results from two distinct analytical approaches—RFC and VQVAE—provides compelling evidence for the pivotal role of specific joints in the classification and correction of movement patterns. These results are harmonious with ground truth observations, validating the approach and underscoring its potential for implementation in clinical settings. This alignment also advocates for the integration of multimodal data in the evaluation process, leveraging both the depth and complexity of kinematic data alongside sophisticated machine learning models to distill the essence of healthy movement. Such integration can lead to more nuanced therapy protocols that target the underpinnings of unhealthy motion, propelling the efficacy of sports rehabilitation into a new era. The methodical discernment of key joints through our dual-analysis not only augments our understanding of human movement biomechanics but also offers actionable insights into the substratum of motion patterns characteristic of sports injuries. By focusing on these critical joints within therapeutic exercises, practitioners can tailor rehabilitation programs that are not only efficacious but also efficient, potentially reducing recovery times and improving outcomes.

This novel approach of correlating RFC-based joint importance with VQVAE-derived embedding distances constitutes a stride towards individualized therapeutic regimens. It emphasizes the necessity for rehabilitation programs to be flexible and adaptable, accommodating the specificities of an individual's biomechanical profile. As such, it is a step forward in the advancement of personalized medicine, particularly within the domain of sports rehabilitation, where such tailored approaches are not a luxury, but a necessity for optimal recovery and return to peak performance.

5. Conclusion & Future work

This study represents a significant step forward in personalized rehabilitation, particularly in the context of sports medicine. By leveraging the strengths of RFC and VQ-VAE, we have distilled crucial insights into the biomechanics of movement, especially as they relate to distinguishing between (un)healthy and compensatory motion patterns. The RFC has provided a fine-grained analysis of the importance of individual joints in various exercises, revealing that not all joints contribute equally to the differentiation between healthy and unhealthy movements. This is invaluable for designing targeted rehabilitation protocols that focus on correcting specific biomechanical deficiencies. Our VQ-VAE analysis further hones this approach by identifying the minimum number of critical joints required to maximize the separation between healthy and unhealthy movement patterns in the latent space. This finding indicates that rehabilitation efforts can be efficiently concentrated on the most impactful areas, potentially leading to improved recovery rates and outcomes.

The synthesis of findings from the RFC and VQ-VAE models has highlighted the utility of a multimodal data analysis approach, incorporating both the rich depth data provided by modern motion capture technology and the sophisticated pattern recognition capabilities of machine learning. Our research emphasizes the potential of such advanced techniques to not only enhance our understanding of complex biomechanical processes but also to translate these insights into practical applications within therapeutic settings. Our study, while pioneering, recognizes the inherent limitations of the approach and the need for further research. The binary classification of movement quality, reliance on specific sensor technology, and the absence of clinical outcome integration all point to areas for future development. Nevertheless, our research has laid the groundwork for subsequent studies that can build on our findings, refine the methodolo-

Figure 4. Qualitative analysis across a temporal sequence of frames for each exercises in standing position, with keypoints superimposed on each frame to capture the full range of motion. The heatmap gradient indicates joint importance based on RFC findings, ranging from low (yellow) to high (black), aiding in the visual comparison of execution quality. The bottom-right corner lists the most significant joints in descending order of importance for each exercise, providing a comprehensive understanding of movement dynamics.

gies, and expand the scope to include more dynamic and spontaneous movements for diverse subjects.

In conclusion, our exploration into the key joints that underpin healthy and pathological movements is a step forward in the generation of personalized, data-driven rehabilitation strategies. By focusing therapeutic interventions on the most significant biomechanical elements identified through our analysis, we can look forward to more effective, efficient, and patient-specific rehabilitation programs that hold the promise of better quality of life for those recovering from sports injuries.

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