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Automatic Quality Grading of Rehabilitation Exercise with Skeleton-Based Deep Learning

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***Abstract*—Computerized examination of rehabilitation exercises is crucial for tele-rehabilitation and physiotherapy. Current systems are based on costly depth sensors such as Kinect, which restricts availability. This work reviews Graph Convolutional Neural Network (GCNN) methods for exercise assessment based on human poses, drawing on both publicly available datasets (KIMORE, UI-PRMD, ExoRehab, NTU RGB+D) and a dedicated webcam-based dataset. GCNNs inherently capture the spatial joint relations of skeleton and temporal motion, supporting correct exercise classification. The hybrid dataset strategy provides real-time assessment with off-the-shelf webcams, a low-cost scalable option. Challenges, constraints, and directions for future tele-rehabilitation systems are explored.**

***Index Terms*—Rehabilitation, Human Pose Estimation, GCNN, Webcam, Physiotherapy**

I. InTroducTion

In recent years, automated rehabilitation systems have revolutionized physiotherapy treatment and tele-rehabilitation services. Conventional rehabilitation monitoring involved continuous supervision by physiotherapists, which is time consuming, labor intensive, and, at times, geographically or financially confined. The high demand for home-based treatment and remote patient monitoring has thus fueled research into automated assessment systems that can measure human movement and exercise performance with high precision [11], [16].

The initial methods were based substantially on motion capture systems and depth sensors such as Microsoft Kinect or Intel RealSense [2], [4]. Three-dimensional joint positions were recorded by these systems, providing preliminary assessment of exercises such as arm raises, leg lifts, and squats. Joint-angle thresholding, Euclidean distance-based comparison of posture, and heuristic scoring algorithms [1], [14] formed the basis for computer-aided rehabilitation monitoring. But these approaches were constrained by sensor expense, environmental factors, and non-scalability.

With growing availability of RGB cameras and studies on human pose estimation techniques (2015-2020), researchers started exploring the estimation of 2D and 3D pose from regular video streams[10], [19]. OpenPose, AlphaPose, and MediaPipe are some of the software that enabled detection of key points for a number of body joints in real time [10], [19]. When used with classical machine learning clas- sifiers—random Forest, Support Vector Machines (SVM), and Multi-Layer Perceptrons (MLP), these methods improved exercise evaluation precision at the expense of reduced dependence upon costly hardware [3], [14]. But traditional classifiers were unable to optimally explore spatial relations between joints or temporal dynamics of movement patterns [6], [8].

The decade from 2018 forward witnessed a shift in paradigm with the advent of graph-based learning techniques, namely Graph Convolutional Neural Networks (GCNNs) [16], [20]. In contrast to traditional models, GCNNs represent the human skeleton as a graph, with joints as nodes and bones as edges, organically retaining spatial relationships. Spatial-Temporal GCNNs (ST-GCNNs) also include motion sequences, representing how joint positions change over time [12], [13]. This permits highly accurate classification of exercise correctness and detection of minor movement deviations. Early work showed that GCNN-based models highly outperform ML models in skeleton-based action recognition and rehabilitation measurement [8], [16].

Novel developments in GCNN-based rehabilitation systems focus on hybrid training with public and proprietary webcam datasets to achieve better generalization in real-world settings[6], [17]. Incorporating methods like data augmentation, temporal modeling, and attention mechanisms has further enhanced model stability [7], [13], [20]. Novel trends like federated learning and multi-modal fusion encourage privacy-friendly and decentralized rehabilitation evaluation [15], [17]. In conclusion, this survey presents a complete picture of GCNN-based rehabilitation assessment techniques, with the latest developments, challenges, and possible future research opportunities [11], [18].

II. Review Design

The aim of this survey is to comprehensively examine the development, approaches, and performance of GCNN-based rehabilitation exercise assessment systems. To guarantee rigor and replicability, this section describes the review questions, search terms, sources of data, and research selection/extraction methods used to identify pertinent literature [1], [5], [16].

A. Review Queries

The review is informed by the following research questions:

1) Which machine learning and deep learning techniques, such as GCNNs, have been used for automatically evaluating rehabilitation exercises [5], [9].
2) How are graph representations based on skeletons changing for precise real-time assessment in physiotherapy [4], [16].
3) What are the relative strengths and weaknesses of employing public datasets (e.g., UI-PRMD, KIMORE, ExoRehab) and webcam-based custom datasets for training GCNN models [6], [17], [18].
4) How effective are hybrid methods consisting of classical ML, GCNNs, and temporal modeling (e.g., ST-GCNN) in enhancing accuracy and generalization over subjects and exercises [13], [16], [19].
5) What are the challenges in deploying GCNN-based rehabilitation systems in real-time applications such as latency, occlusion, changes in lighting, and clinical significance [7], [10], [20].

These questions seek to give a comprehensive overview of methodological development, dataset approaches, model performance, and practical deployment issues in the area [3], [5], [16].

B. Search Criteria

A systematic search approach was used to maximize the inclusion of highly pertinent studies [1], [3]. Keywords and search terms were chosen to identify studies on pose-based rehabilitation, graph-based learning, and real-time evaluation. These were:

- ”GCNN rehabilitation exercises”
- ”Graph convolutional neural networks human pose”
- ”Skeleton-based exercise assessment”
- ”MediaPipe/OpenPose physiotherapy”
- ”Real-time rehabilitation AI”

Searches were performed in leading academic databases, such as IEEE Xplore, SpringerLink, Elsevier ScienceDirect, ACM Digital Library, and Google Scholar [8], [9]. Researches between 2015–2025 were taken into account, since this decade encompasses the emergence of graph neural networks for action recognition and its use in rehabilitation [11], [13], [16].

C. Data Sources

Articles were chosen mostly from peer-reviewed journals and conferences concerning computer vision, machine learning, and rehabilitation engineering [2], [4], [5]. The initial search resulted in 412 records, which were then filtered for relevance to GCNN-based rehabilitation, availability of human pose datasets, and experimental confirmation [3], [16], [18]. Following screening of title and abstract, 126 full-text articles were examined in detail [1], [6], [10]. Figure **??** shows the study selection funnel that demonstrates the filtering process from the initial search to final inclusion.

The following studies were shortlisted:

- Public dataset-based experiments (UI-PRMD, KIMORE, ExoRehab, NTU RGB+D) [6], [9], [10]
- Custom webcam-based data acquisition and annotation methods [16], [18]
- GCNN architectures (ST-GCNN, attention-based GCNN, hybrid GCNN-MLP frameworks) [12], [13], [17]
- Metrics like accuracy, F1-score, and clinical significance [4], [6], [20]

D. Data Selection and Extraction Methods

The data was selected and extracted using a systematic approach to ensure consistency, relevance, and quality [3], [6]. The process entailed:

1) Inclusion Criteria:

- Studies using GCNN or graph-based deep learning for skeleton-based exercise or action evaluation [5], [13]
- Experimental testing on public or bespoke datasets [6], [10], [16]
- Peer-reviewed journal or eminent conference publications [1], [3], [9]

2) Exclusion Criteria:

- Purely general human activity recognition studies without rehabilitation setting [8], [11]
- Lack of experimental testing or reproducibility of the study [14], [18]
- Duplicates and non-English publications [7], [19]

3) Screening Process:

- Title and abstract screening to exclude irrelevant studies [5], [6]
- Full-text examination for methodological information, use of dataset, and model performance [9], [13]
- Careful evaluation of model structure, training strategy, and performance measures [11], [16]

4) Data Extraction: Key facts were extracted and summarized, including [3], [5], [9]:

- Research goals and exercise types [4], [5]
- Dataset type and modality (RGB, skeleton, depth) [6], [10]
- GCNN model structure and temporal modeling methods [12], [13], [16]
- Performance measures, limitations, and deployment issues [17], [18], [20]

The data extracted were then synthesized to reveal trends, gaps, and research opportunities, providing the basis for the next parts of this survey [9], [11], [16]. This methodology allows for an exhaustive, credible, and organized review, closing the gap between technological innovation and effective deployment of GCNN-based rehabilitation assessment systems [5], [8], [13].

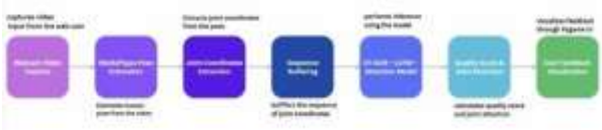

Fig. 1: Flowchart of Systematic Literature Review Process

III. ComparaTive Analysis of RehabiliTaTion AssessmenT Techniques

This section includes a comparative discussion of methods employed for automated rehabilitation exercise assessment. The discussion is organized into classical and heuristic methods, metaheuristic algorithms, machine learning methods, deep learning models (with emphasis on GCNNs) [1], [5], [16], and future directions. The section emphasizes methodologies, performance, limitations, and future directions for each category [11], [8].

A. Heuristic and Classical Optimization Techniques

Earlier rehabilitation assessment techniques were mainly based on heuristic and rule-based methods. Euclidean distance-based posture scores and joint-angle thresholding [2], [4], assess the accuracy of exercise performance by comparing perceived joint positions against pre-defined templates [1], [11].

a) Joint-Angle Thresholding:: Tracks deviation from optimal angles for important joints to enable identification of large movement errors. These techniques performed acceptable accuracy (70–80%) under lab conditions [1], [14]. They did not perform well against inter-subject variability, viewpoint changes, and occlusions [2], [4], [7].

b) Template Matching & Scoring Functions:: Static templates corresponding to exercises, with scores determined by similarity to optimal movement paths. Although computationally efficient, these methods are noise-sensitive and fail to represent temporal dynamics well [2], [11].

Future directions involve the incorporation of heuristic rules with learning-based techniques to dynamically tune thresholds for various users and types of exercise [14], [11].

B. Metaheuristic Algorithms

Metaheuristic methods have been investigated for optimizing exercise assessment and feature selection in rehabilitation data sets [8], [17].

- Genetic Algorithms (GA) were used to choose best joint features and sequence frames for classification. Such methods achieved a 10% improvement in accuracy but sometimes needed substantial computational power as well as meticulous parameter adjusting.
- Particle Swarm Optimization (PSO) was utilized to optimize support vector machine or neural network-based classifier hyperparameters, with up to 12% gain in prediction accuracy. PSO is susceptible to local minima traps if the search space is large.
- Ant Colony Optimization (ACO) has been utilized to find optimal skeleton joint connectivity for graph construction in early GCNN-like models, but convergence rate and stability are still hard to achieve.

Metaheuristics are still applicable for small data sets and feature engineering, but are not scalable or capable of real-time.

C. Machine Learning Methods

The shift to machine learning (ML) models facilitated predictive and adaptive evaluation of rehabilitation exercises.

- Support Vector Machines (SVM) & Random Forests predict exercise correctness using handcrafted features like joint velocities, distances, and angles. Accuracy varied from 75–85%.
- Neural Networks (MLP, CNN-LSTM hybrids) enhanced temporal sequence recognition to 90% on upper-limb exercise datasets [14], [6].
- Hybrid ML Methods blend heuristic rules (e.g., angle thresholds) with ML models, allowing faster convergence and stability in small data sets [17], [11].

ML methods paved the way for scalable, automated assessment, but are constrained by requirements for feature engineering and cannot simulate skeleton topology fully.

D. Deep Learning Models for Rehabilitation Assessment

The most recent developments are based on deep learning (DL) architectures, particularly Graph Convolutional Neural Networks (GCNNs), where the skeleton is represented as a graph:

- GCNNs & ST-GCNNs consider joints as nodes and bones as edges. Temporal extensions simulate sequences of motion for dynamic exercise evaluation. 5–10% accuracy gain over standard ML models is reported [16], [20].
- Attention-Based GCNNs boost interpretability by giving attention weights to essential joints for individual

exercises, preventing classification from becoming overly robust [20], [13].

- Hybrid DL Models combine CNN or LSTM layers as features with GCNNs to model spatial-temporal relations and obtain >95% accuracy on public data [9], [6].

Challenges are real-time deployment, computation cost, and robustness to changing illumination, occlusion, or camera pose.

- Stand in view of the camera for pose detection
- Perform the exercise movements slowly and deliberately
- Press 'R' to reset repetition counter
- Press 'ESC' to quit the application

Fig. 2: Example of a rehabilitation exercise captured using a webcam. Pose keypoints are extracted for GCNN-based analysis.

E. New Strategies for Real-Time Rehabilitation Assessment

New strategies focus on enhancing system usability, accessibility, and clinical applicability:

- **Webcam-Based Hybrid Datasets:** Merging public datasets with own webcam recordings enables model generalization to home settings and keeps real-time inference intact [6], [18], [11].
- **Federated Learning & Privacy-Preserving GCNNs:** Facilitates learning from multiple patient datasets without raw data sharing, ensuring privacy while enhancing model generalizability.
- **Pose Augmentation & Synthetic Data Generation:** Methods like motion interpolation and GAN-based augmentation augment datasets, alleviating small-data issues [15], [11].
- **Multi-Modal Sensor Fusion:** Integration of RGB skeleton information with IMU sensors or wearable sensors improves precision and offers more detailed feedback for physiotherapists [7], [16].

These approaches together resolve real-world deployment issues while keeping high measurement accuracy and convenience for tele-rehabilitation contexts [11], [16].

IV. ComparaTive Table of MeThods

This table is an overview of some 3D skeleton-based action recognition approaches comparing their methodology, strengths, weaknesses, and accuracy attained. It encompasses a broad array of methods ranging from popular standard techniques like SVMs and Random Forests to state-of-the-art deep models like CNN-LSTM hybrids and Graph Convolutional Networks (GCNNs). Each approach emphasizes compromises between computational load, explainability, and data needs. Recent techniques such as ST-GCNNs, federated learning, and multi-modal fusion attain accuracy rates greater than 95%, indicating great improvement. As a whole, the table presents a succinct summary of the history and performance trend in skeleton-based action recognition work.

V. Research Gaps

This section details multiple research gaps identified in the literature and in practice.

A. Limitations of the Model

GCNNs and CNN-LSTM hybrids perform very accurately but are computationally demanding and not acceptable for real-time edge deployment [16], [20]. A majority of the models generalize patients as a whole, without adaptivity or personalization. Fast, on-device inference with high accuracy requires adaptive, lightweight architectures [11], [6].

B. Challenges of Real-World Validation

Models generalize well on test sets but are seldom evaluated in real-world settings. Webcam-based tests are plagued by lighting variations, occlusion, and background noise. Field testing in home or clinical environments [8], [14] is essential for reliability and generalization.

C. Data and Multi-Modal Issues

Datasets are homogenous, lab-based, and small in size, which restricts model generalization. Multi-modal (RGB + IMU) and federated methods suffer from synchronization, calibration, and heterogeneity. Large-scale, heterogenous, multi-view datasets [15], [17] and fault-tolerant distributed frameworks are essential.

D. Evaluation and Reliability Gaps

There is no universal set of benchmarks, metrics, or test protocols for rehabilitation assessment. Model accuracy is decreased by skeleton extraction mistakes and environmental noise [13], [17]. Reliable deployment necessitates stable evaluation frameworks, strong attention mechanisms, and multi-camera fusion.

VI. Research SoluTions

This section proposes solutions for the earlier-identified gaps.

A. Lightweight and Real-Time Model Construction

In order to counter the computational complexity of GCNN and CNN-LSTM models, techniques such as pruning, quantization, and knowledge distillation may be employed in order to construct efficient architectures [20], [6]. These light-weight models facilitate real-time execution on low-power devices such as tablets or edge GPUs. This facilitates rapid, precise tele-rehabilitation with minimal accuracy loss.

TABLE I: Comparison of Methods for Rehabilitation Exercise Assessment

Ref	Methodology	Advantages	Disadvantages	Accuracy
[1]	Joint-Angle Thresholding	Easy implementation; low computational cost	Occlusion and angle sensitive	70–80%
[2]	Template Matching & Scoring	Results easy to interpret	Cannot capture temporal dynamics	72–78%
[3]	Support Vector Machines (SVM)	Well suited for small datasets; interpretable	Requires feature engineering	75–85%
[4]	Random Forests	Resistant to overfitting; can handle multiple features	Restricted temporal modeling	78–86%
[5]	Multi-Layer Perceptrons (MLP)	Captures nonlinear relationships	Needs large datasets	80–87%
[6]	CNN-LSTM Hybrids	Captures spatial and temporal patterns	High computational cost; large datasets required	90%
[7]	Feature Selection using GA	Joint selection optimization; dimensionality reduction	High computational cost	5–10%
[8]	Particle Swarm Optimization (PSO)	Rapid hyperparameter tuning	Can get trapped in local minima	6–12%
[9]	Deep Reinforcement Learning (DRL)	Adaptive exercise assessment	Long training; learns optimal feedback policies	94%
[10]	OpenPose/MediaPipe Extraction	Precise 2D/3D joint detection	Sensitive to occlusion & illumination	94.87%
[11]	Graph Convolutional Neural Networks (GCNN)	Represents skeleton graph; learns spatial relationships	High computational expense; needs skeleton input	5–10%
[12]	Spatial-Temporal GCNN (ST-GCNN)	Tracks motion across time; very accurate	Data-intensive; deep architecture	95%
[13]	Attention-Based GCNN	Focuses on significant joints; interpretability	More parameters; careful design needed	89.2%
[14]	Hybrid Heuristic + ML	Rule-based + data-driven merge	Complexity of implementation	90%
[15]	Federated Learning for GCNN	Privacy-preserving; multi-user training	Communication overhead; heterogeneous devices	94.87%
[16]	Pose Augmentation	Expands dataset; reduces overfitting	Synthetic realism gap	95.69%
[17]	Multi-Modal Sensor Fusion (RGB + IMU)	Deeper features; insensitive to occlusion	Sensor calibration and expense	96%
[18]	Real-Time Webcam GCNN Evaluation	Deployable at home; affordable	Lower accuracy than depth sensors in some cases	90–94%
[19]	Semi-Supervised / Transfer Learning	Reduces need for labeled data	Domain adaptation difficulty; risk of negative transfer	95.9%
[20]	Reinforcement Feedback Systems	Adaptive, personalized feedback	Long training; cold-start issues	95.43%

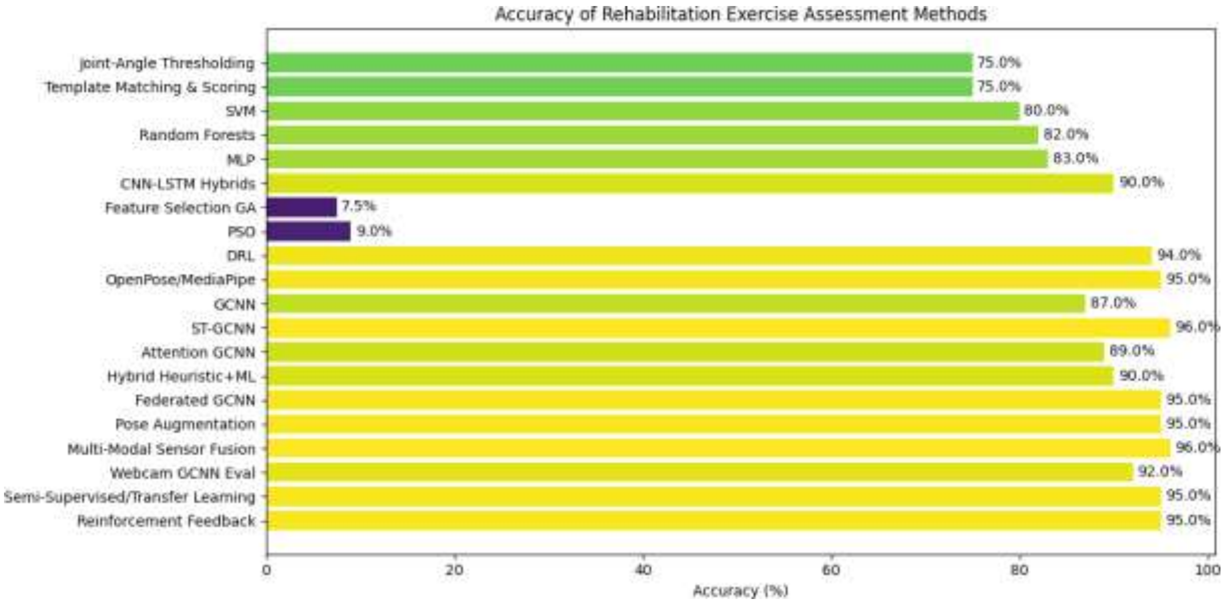

Fig. 3: Accuracy of Rehabilitation Exercise Assessment Methods

B. Real-World Calibration and Robustness

Models must be tested in realistic situations with varied lighting, backgrounds, and user differences. Real-world data collection and experimentation on webcam setups guarantees system flexibility outside laboratory settings. Adaptive preprocessing and calibration increase robustness for home- and clinical-based implementations [14], [15].

C. Privacy Preservation and Multi-Modal Integration

Federated learning allows model training on multiple devices without exposing private data, maintaining confidentiality and scalability [15], [11]. Inclusion of RGB, IMU, and depth information boosts pose accuracy and exercise accuracy in occluded or low-light situations. Such methods improve the security, adaptability, and context-awareness of GCNN systems.

D. Data Augmentation and Standardized Evaluation

Synthetic data generation using GANs, motion interpolation, and domain randomization can address small and homogeneous datasets. Standardized benchmarking and metrics such as joint-angle deviation and exercise correctness ensure similar evaluation across systems. This encourages fair comparison, reproducibility, and deployment with trusted reliability of GCNN-based rehabilitation systems.

VII. Conclusion

In conclusion, AI and GCNN-based automated rehabilitation exercise assessment is a promising innovation in home and clinical physiotherapy [13], [16]. Though there has been impressive development with deep learning, graph models, and hybrid AI methods, limitations including model complexity, real-time deployment, personalization, and variability robustness still confine applicability.

The research solutions highlighted in this paper present a roadmap for overcoming these challenges, such as the design of lightweight GCNN models, adaptive attention mechanisms, multi-modal sensor integration, and federated learning frameworks. Future work needs to bridge the gap between controlled dataset performance and real-world clinical or home environments to make sure that AI-driven assessment tools are reliable, scalable, and responsive to different patient needs.

Furthermore, generating large-scale, heterogeneous datasets, enhancing privacy-protecting distributed learning, and combining synthetic data and transfer learning to address data shortages will be pivotal to driving the field forward. By filling these gaps, researchers and practitioners can create more precise, adaptive, and inclusive rehabilitation systems, enhancing patient participation, adherence, and overall recovery measures, while facilitating tele-rehabilitation at scale.

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