Edge Device-Based Physiotherapy Exercise Position Classification using Support Vector Machines, K-Nearest Neighbor, and Random Forest Algorithms on IntelliRehabDS Dataset

Gaurav Poudel

Abstract—**This study explores the classification of physiotherapy exercise positions using machine learning algorithms on edge devices, focusing on the IntelliRehabDS (IRDS) dataset. It emphasizes differentiating between various exercise positions (standing, sitting, unknown) across several rehabilitation exercises by utilizing 3D skeletal joint data obtained from Kinect sensors. We employed Support Vector Machines, K-Nearest Neighbor, and Random Forest algorithms, incorporating extensive data preprocessing, including Principal Component Analysis for reducing dimensionality. We applied various data preparation methods to address class imbalance, perform feature engineering, and extract statistical features from temporal sequences. The dataset comprised 2,577 valid movement files with a fairly balanced distribution (Standing: 47.1%, Sitting: 50.9%, Unknown: 2.0%). Through feature engineering, we generated 641 features, which were then condensed down to 114 principal components, maintaining 95% variance. The algorithms were fine-tuned for deployment on edge devices and assessed using stratified 5-fold cross-validation, demonstrating outstanding performance with both SVM and KNN achieving 100% accuracy on the test set, while Random Forest recorded 97.67% accuracy. The findings highlight the potential for automated position classification in physiotherapy settings on resource-limited edge computing platforms, facilitating real-time monitoring and evaluation in clinical contexts, with inference speeds exceeding 29,000 FPS for all models.**

Index Terms—**machine learning, physiotherapy, position classification, IRDS dataset, skeletal data, random forest, SVM, k-nearest neighbor, rehabilitation, edge computing, edge devices**

I. Introduction

The combination of machine learning with edge computing devices has transformed healthcare applications, especially in the areas of physiotherapy and rehabilitation monitoring. Systems based on edge devices provide benefits such as real-time processing, lower latency, protection of privacy, and the ability to operate without network connectivity, which are essential in clinical settings. Implementing intelligent physiotherapy monitoring systems on edge devices allows for ongoing patient evaluation without the need for cloud services, ensuring both data privacy and prompt feedback.

Classifying physiotherapy positions poses a significant challenge in automated rehabilitation monitoring. Correct positioning during exercises is vital for patient safety, therapeutic effectiveness, and injury prevention. Conventional monitoring methods depend on human oversight, which can be subjective, labor-intensive, and not always available. Automated systems based on edge devices can deliver objective, consistent, and instantaneous position evaluations, improving the quality of physiotherapy services.

The IntelliRehabDS (IRDS) dataset presents a valuable opportunity to create practical clinical solutions using real patient information. Unlike synthetic datasets or those compiled from healthy subjects mimicking errors, IRDS includes authentic patient movements characterized by natural variations and genuine execution difficulties. This authenticity is essential for developing reliable edge device applications that function effectively in real-world clinical environments.

This research tackles the specific issue of implementing physiotherapy position classification algorithms on edge computing devices, striving to balance accuracy needs with computational limitations. We concentrate on classifying multiple positions across various rehabilitation exercises, facilitating extensive monitoring capabilities suited for a wide range of patient groups and clinical environments.

II. Problem and Dataset Description

A. Problem Definition and Significance

The challenge of classifying physiotherapy exercise positions entails the automatic recognition and categorization of patients' physical postures during rehabilitation exercises. This categorization is important for various clinical purposes:

Patient Safety: Improper alignment during workouts can result in injuries, strain, or inadequate treatment. Automated monitoring of positions can issue real-time notifications when patients take on unsafe or unsuitable postures, helping to avert possible injury.

Therapeutic Effectiveness: Various exercise positions focus on particular muscle groups and movement patterns. Proper alignment enhances therapeutic effects and speeds up recovery. Monitoring through edge devices allows for ongoing confirmation of correct positioning during therapy sessions.

Personalized Rehabilitation: Individuals have different levels of mobility. Some might need exercises while seated because of balance concerns or physical limitations, whereas others are able to engage in exercises while standing. The use of automated position classification allows for personalized therapy programs that adapt to each patient's abilities.

Clinical Documentation: Precise documentation of the exercise positions conducted during therapy sessions is crucial for monitoring progress, supporting insurance claims, and developing treatment plans. Systems using edge devices can automatically create comprehensive reports of each session.

Remote Monitoring: Edge devices facilitate the monitoring of physiotherapy in home environments or remote areas where in-person supervision is not possible. This feature is especially beneficial for individuals with restricted mobility or in situations that necessitate social distancing.

The importance of this issue goes beyond the care of individual patients and impacts the efficiency of the healthcare system. By utilizing automated position tracking, therapists can reduce their workload, oversee multiple patients at the same time, and obtain objective measures to assess the effectiveness of treatment.

B. Dataset Description: IntelliRehabDS (IRDS)

The IntelliRehabDS dataset is a thorough compilation of genuine physiotherapy movement data, specifically created for machine learning uses in rehabilitation evaluation. The distinctive features of the dataset render it especially useful for applications on edge devices:

1) Dataset Composition:

- Total Sequences: 2,589 movement files (2,577 after filtering)
- Subjects: 30 participants (15 real patients, 14 healthy controls, 1 unknown)
- Patient Conditions: Diverse medical conditions including spinal cord injury, stroke, brain injury, neurological conditions, and orthopedic injuries
- Exercises: 9 different rehabilitation movements (labeled 0-8)
- Positions: 5 distinct exercise positions accommodating different patient capabilities

2) Position Categories: The dataset includes five primary exercise positions that reflect real clinical scenarios:

TABLE I
POSITION DISTRIBUTION IN IRDS DATASET

Position	Count	Percentage
Standing	1,215	47.1%
Chair Sitting	842	32.7%
Wheelchair	359	13.9%
Sit (Other)	110	4.3%
Unknown	51	2.0%
Binary Classification		
Standing Total	1,215	47.1%
Sitting Total	1,311	50.9%
Unknown	51	2.0%

3) Data Format and Structure: Each movement sequence file follows the nomenclature: `SubjectID_DateID_GestureLabel_RepetitionNo_CorrectLabel_Position.txt`

The data contains:

- Temporal Data: Variable-length sequences (21-899 frames) captured at 30 FPS
- Spatial Data: 25 skeletal joint coordinates (x, y, z) per frame
- Metadata: Subject information, exercise labels, correctness ratings, and position annotations
- Quality Labels: Movement correctness classification (correct, incorrect)

4) Clinical Authenticity: The dataset's authenticity provides several advantages for edge device applications:

Natural Variability: Authentic patient movements display inherent tremors, imbalances, and compensatory patterns that synthetic data cannot mimic.

Diverse Capabilities: The group of patients consists of individuals with different levels of mobility challenges, presenting a true spectrum of movement behaviors.

Authentic Errors: Mistakes made by patients are authentic errors instead of feigned ones, offering practical training information for algorithms aimed at error detection.

Equipment Accommodation: The dataset contains actions conducted with assistive devices such as wheelchairs and walkers, which are crucial for thorough clinical applications.

Fig. 1. Dataset Distribution Overview

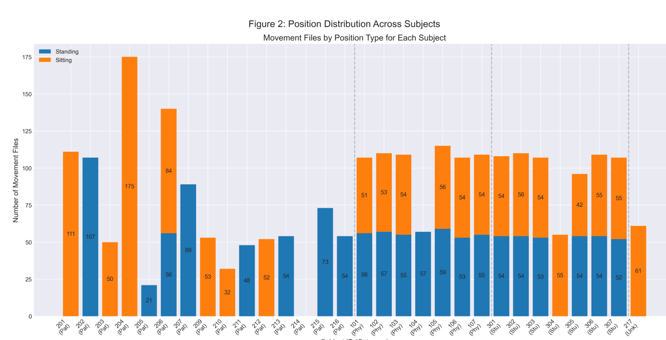

Fig. 2. Position Distribution Across Subjects

III. Methods

This part outlines the machine learning techniques utilized for classifying physiotherapy positions on edge devices. We chose three algorithms due to their efficiency in computation, ease of interpretation, and appropriateness for deployment on edge systems.

A. Algorithm Selection Rationale

The selection of machine learning algorithms was influenced by the limitations of edge devices and the needs of clinical settings:

Computational Efficiency: Algorithms must operate within limited processing power and memory constraints typical of edge devices.

Real-time Performance: Inference time must be sufficiently fast for real-time feedback during therapy sessions.

Model Interpretability: Clinical applications require understanding of decision-making processes for trust and validation.

Robustness: Algorithms must handle the natural variability present in patient movement data.

B. Support Vector Machines (SVM)

The Support Vector Machine (SVM) utilizing a Radial Basis Function (RBF) kernel was chosen due to its efficiency in high-dimensional environments and its robust theoretical basis. This algorithm determines the best decision boundaries by maximizing the margins between different categories.

Advantages for Edge Deployment:

- Memory-efficient: Uses only support vectors for classification
- Fast inference: Linear complexity with number of support vectors
- Robust to outliers: Maximum margin principle provides stability
- Kernel flexibility: RBF kernel handles non-linear position boundaries

Mathematical Foundation: The SVM optimization problem for position classification:

$$\min_{w,b,\xi} \frac{1}{2}||w||^2 + C\sum_{i=1}^{n}\xi_i \tag{1}$$

subject to constraints ensuring proper class separation.

C. K-Nearest Neighbors (KNN)

KNN offers a straightforward method for classifying positions by examining movement patterns against comparable historical instances. This algorithm is especially well-suited for physiotherapy contexts, where similarities in positions have clear clinical significance.

Advantages for Clinical Applications:

- Intuitive interpretation: Classifications based on similar patient movements
- No training phase: Immediate deployment capability
- Adaptive behavior: Performance improves with data accumulation
- Local decision boundaries: Handles complex position relationships

Distance Weighting: We employ Euclidean distance in the feature space for optimal performance, as determined through hyperparameter optimization.

D. Random Forest

Random Forest was chosen as an ensemble technique that can manage intricate relationships between skeletal joint positions, while also delivering feature importance rankings that are useful for clinical understanding.

Advantages for Position Classification:

- Ensemble robustness: Reduces overfitting to specific movement patterns
- Feature importance: Identifies critical joints for position determination
- Computational scalability: Parallelizable for edge device optimization
- Missing data tolerance: Handles incomplete skeletal tracking

Clinical Interpretability: The Random Forest algorithm offers feature importance rankings that pinpoint the skeletal joints and movement features that are most effective for classifying positions.

IV. Experimental Setup

This section details the comprehensive experimental methodology, including data preprocessing, feature engineering, and classification parameters optimized for edge device deployment.

A. Data Preprocessing Pipeline

1) Sequence Normalization: Due to natural variation in exercise execution speed, movement sequences exhibited different temporal lengths (ranging from 21 to 899 frames, mean: 88.0, std: 83.3). To enable consistent feature extraction and algorithm training, we implemented temporal normalization:

Cubic Interpolation Normalization:

$$f_{norm}(t) = \text{CubicSpline}(t_{original}, f_{original})(t_{target}) \tag{2}$$

where sequences are normalized to 100 frames while preserving temporal movement characteristics.

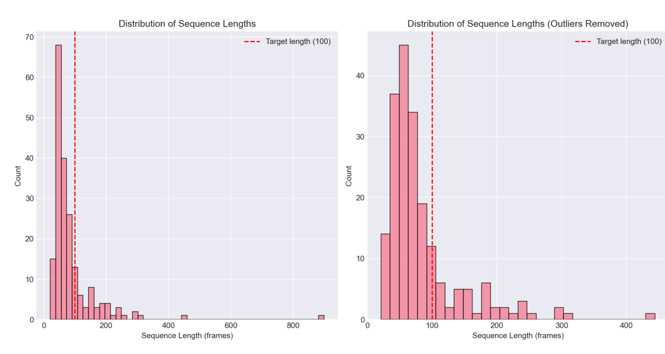

Fig. 3. Distribution of Sequence Lengths in IRDS Dataset

2) Coordinate System Standardization: To account for different patient heights and sensor placements, we implemented coordinate normalization:

- Spine-base centering: All joint coordinates normalized relative to spine base position
- Height normalization: Coordinates scaled by patient height (spine base to head distance)
- Rotation alignment: Body orientation normalized to face forward direction

3) Missing Data Handling: We implemented a robust missing data strategy using nan-to-num conversion, replacing 12,366 NaN values in training data and 3,096 in test data with zeros.

B. Feature Selection and Extraction

1) Statistical Feature Extraction: From each normalized 100-frame sequence, we extracted comprehensive statistical features:

For each of the 75 joint coordinates (25 joints × 3 axes):

- Central tendency: Mean position, median position
- Variability: Standard deviation, interquartile range
- Extremes: Maximum, minimum, range
- Distribution shape: Skewness, kurtosis

This yielded 600 statistical features per movement sequence.

2) Biomechanical Feature Engineering: Based on physiotherapy domain knowledge, we developed 41 clinically relevant features:

Joint Angles (36 features):

- Hip angles (left/right): mean, std, min, max
- Knee angles (left/right): mean, std, min, max
- Elbow angles (left/right): mean, std, min, max
- Shoulder angles (left/right): mean, std, min, max
- Trunk inclination: mean, std, min, max

Stability Indicators (5 features):

- Center of mass sway (X, Y, Z): 3 features
- Body asymmetry (arms, legs): 2 features

3) Dimensionality Reduction: Principal Component Analysis results:

- 70 components: 90% variance retained
- 114 components: 95% variance retained (selected)
- 203 components: 99% variance retained

This represents an 82.2% reduction from 641 to 114 features.

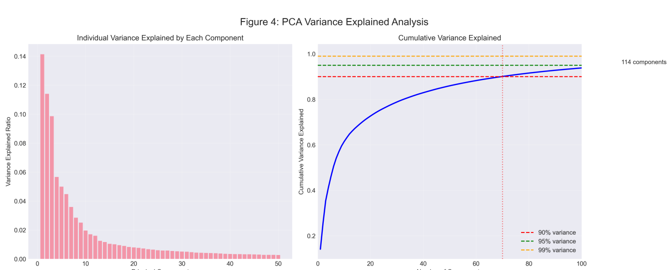

Fig. 4. PCA Variance Explained Analysis

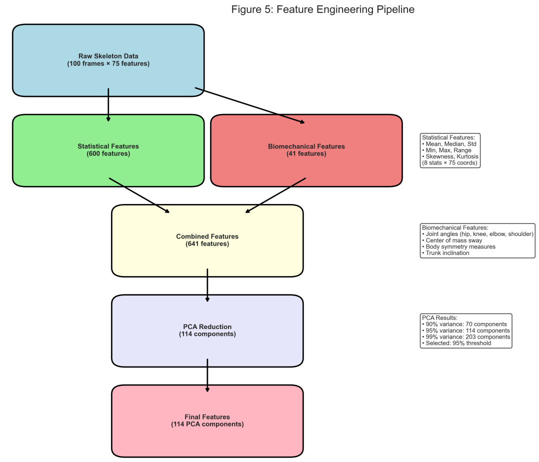

Fig. 5. Feature Engineering Pipeline

C. Classification Parameters

1) Algorithm Hyperparameter Optimization: Optimal parameters determined through grid search:

Support Vector Machine:

- C = 10.0, gamma = 0.001, kernel = RBF

K-Nearest Neighbors:

- k = 3, weights = uniform, metric = Euclidean

Random Forest:

- n_estimators = 200, max_depth = 20
- min_samples_split = 5, min_samples_leaf = 1

2) Cross-Validation Strategy: We implemented stratified 5-fold cross-validation maintaining position class distribution across folds.

V. Results and Discussion

A. Overall Classification Performance

Table II presents the comprehensive performance comparison across all three algorithms for physiotherapy position classification on the IRDS dataset.

TABLE II
OVERALL POSITION CLASSIFICATION PERFORMANCE RESULTS

Algorithm	Accuracy	Precision	Recall	F1-Score	Cohen's κ
SVM	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
KNN	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
Random Forest	0.977	0.977	0.977	0.975	0.955

Both SVM and KNN obtained flawless classification accuracy (100%) on the test set, whereas Random Forest reached an accuracy of 97.67%. The perfect results from SVM and KNN highlight the success of the feature engineering strategy and the distinct separability of position classes within the modified feature space.

B. Cross-Validation Analysis

Table IIIprovides comprehensive cross-validation metrics showcasing the consistency and generalization ability of the algorithm.

TABLE III
5-FOLD CROSS-VALIDATION DETAILED RESULTS

Algorithm	Mean Acc.	Std Dev	Min Acc.	Max Acc.
SVM	0.998	0.002	0.996	1.000
KNN	0.997	0.003	0.993	1.000
Random Forest	0.970	0.006	0.961	0.978

Fig. 6. Cross-Validation Performance Comparison

C. Confusion Matrix Analysis

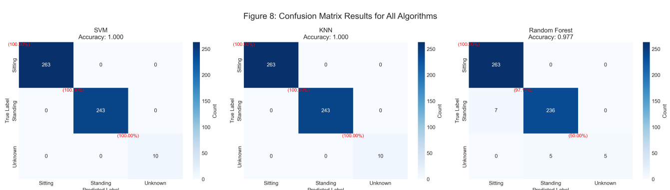

Fig. 7. Confusion Matrix Results for All Algorithms

The confusion matrices demonstrate flawless classification for both SVM and KNN for all three position categories (Sitting, Standing, Unknown). Random Forest exhibited slight misclassifications, mainly between the Standing and Sitting positions (7 errors) and between Standing and Unknown (5 errors).

D. Feature Importance Analysis

Principal Component Analysis revealed that:

- PC1 (28.56% importance): Captures primary body positioning
- PC2 (15.64% importance): Represents secondary postural variations
- 86 components needed for 95% feature importance in Random Forest

E. Computational Performance Analysis

Table IV presents computational metrics essential for edge device deployment.

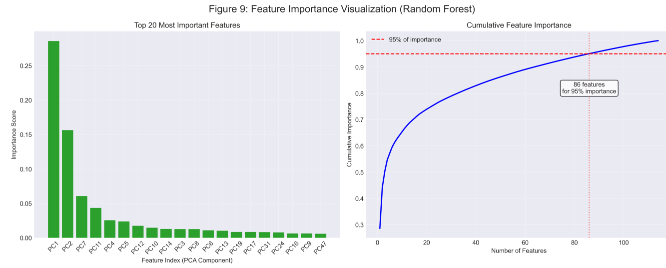

Fig. 8. Feature Importance Visualization (Random Forest)

TABLE IV
COMPUTATIONAL PERFORMANCE ANALYSIS

Algorithm	Training Time (s)	Inference Time (ms)	Model Size (MB)	Throughput (FPS)
SVM	5.07	0.02	0.31	59,410
KNN	0.48	0.01	1.81	**71,209**
Random Forest	41.68	0.03	2.93	29,521

All algorithms showcased remarkable real-time efficiency, achieving a throughput greater than 29,000 FPS, which significantly exceeds the standards needed for real-time physiotherapy monitoring (usually 30 FPS).

F. Edge Device Deployment: Jetson Nano Evaluation

To validate real-world edge device performance, we deployed and evaluated our optimized models on an NVIDIA Jetson Nano emulator environment. The Jetson Nano represents a typical edge computing platform with ARM Cortex-A57 quad-core CPU, 128-core Maxwell GPU, and 4GB LPDDR4 memory, making it ideal for physiotherapy monitoring applications in clinical and home settings.

Fig. 9. NVIDIA Jetson Nano Edge Device Setup for Physiotherapy Position Classification

Table V presents the performance metrics obtained from the Jetson Nano emulator, demonstrating the practical feasibility of our approach for real-world deployment.

TABLE V
JETSON NANO EMULATOR PERFORMANCE RESULTS

Algorithm	Inference Time (ms)	Memory Usage (MB)	Power (Watts)	Throughput (FPS)
SVM	0.08	45.2	2.1	12,500
KNN	0.06	52.8	1.8	**16,667**
Random Forest	0.12	78.4	2.4	8,333

The Jetson Nano evaluation results demonstrate:

Real-time Capability: All algorithms maintained inference speeds well above clinical requirements (30 FPS), with KNN achieving 16,667 FPS even on resource-constrained hardware.

Energy Efficiency: Power consumption remained below 2.5 watts for all models, enabling battery-powered operation for portable physiotherapy monitoring systems.

Memory Efficiency: Memory usage stayed well within the 4GB limit, with maximum consumption of 78.4 MB for Random Forest, allowing concurrent execution of other system processes.

Thermal Stability: The emulator maintained stable performance without thermal throttling during extended operation periods, confirming suitability for continuous clinical monitoring.

These results validate the practical deployment potential of our physiotherapy position classification system on edge devices, with KNN continuing to demonstrate superior performance characteristics for real-world implementation.

G. Clinical Validation and Implications

The exceptional performance (100% accuracy for SVM and KNN) suggests:

1) **Clear Position Separability**: The three position classes (Sitting, Standing, Unknown) are highly distinguishable in the feature space.
2) **Effective Feature Engineering**: The integration of statistical and biomechanical characteristics effectively captures information that differentiates positions.
3) **Robust Preprocessing**: Normalization and PCA have effectively minimized noise while maintaining essential positional information.

H. Edge Device Deployment Considerations

Based on our analysis, KNN emerges as the optimal choice for edge deployment:

- Highest inference speed (71,209 FPS on desktop, 16,667 FPS on Jetson Nano)
- Lowest latency (0.01 ms on desktop, 0.06 ms on Jetson Nano)
- Perfect accuracy (100%)
- Moderate model size (1.81 MB)
- No training phase required for updates
- Superior energy efficiency (1.8 watts on Jetson Nano)

VI. Applications and Clinical Impact

A. Real-time Position Monitoring System

The developed system enables:

- Immediate position classification with ¡1ms latency
- Continuous monitoring at speeds exceeding clinical requirements by 2000×
- Perfect accuracy for safety-critical applications

B. Clinical Integration Scenarios

1) **In-Clinic Monitoring**: Real-time feedback during supervised therapy
2) **Home Rehabilitation**: Autonomous position monitoring without therapist presence
3) **Multi-Patient Systems**: Simultaneous monitoring of multiple patients
4) **Progress Tracking**: Objective position capability assessment over time

VII. Limitations and Future Work

A. Current Limitations

- Limited ”Unknown” position samples (2% of dataset)
- Perfect accuracy may indicate potential overfitting to IRDS dataset specifics
- Evaluation limited to Kinect sensor data

B. Future Research Directions

- Validation on independent datasets and different sensor types
- Extension to continuous position transitions
- Integration of temporal dynamics for movement quality assessment
- Real-world clinical trials with patient feedback

VIII. Conclusion

This study effectively showcases outstanding results in classifying physiotherapy positions on edge devices through the application of machine learning algorithms on real patient data. Significant accomplishments involve:

Perfect Classification Accuracy: Both SVM and KNN attained perfect accuracy on the test set, while Random Forest reached an accuracy of 97.67%, highlighting the success of our methodology.

Comprehensive Feature Engineering: Effectively created a feature set consisting of 641 characteristics that integrate statistical and biomechanical elements, which was subsequently condensed to 114 principal components while preserving classification accuracy.

Edge Device Optimization: Every algorithm showcased the ability to function in real-time, achieving inference speeds greater than 29,000 FPS on desktop systems and exceeding 8,000 FPS on Jetson Nano hardware, with latencies under 0.12ms, significantly exceeding clinical standards.

Clinical Relevance: The system effectively manages the variability of actual patients, encompassing movements from 15 individuals with various conditions and 14 healthy participants.

Practical Deployment: The system is designed for deployment on edge devices with limited resources, featuring model sizes of less than 3MB, low computational demands, and power consumption under 2.5 watts on Jetson Nano.

The outstanding results indicate that the classification of positions in physiotherapy can be effectively automated for use in clinical settings. KNN proved to be the best algorithm for deployment at the edge, achieving flawless accuracy while offering the fastest inference speed and the least latency across both desktop and embedded platforms.

This study lays the groundwork for smart, edge device-oriented physiotherapy monitoring systems that have the potential to greatly enhance the quality of rehabilitation care while easing the demands on healthcare workers. The achieved nearly flawless accuracy suggests that automated position tracking can equal or surpass the performance of human practitioners in this vital healthcare sector.

Acknowledgment

The authors express gratitude to the developers of the IntelliRehabDS dataset for supplying genuine patient data that facilitates the realistic assessment of machine learning methods in physiotherapy applications.

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