Human Activity Recognition and Biomechanical Analysis Using MPU6050 IMU Data for Anthropodic Movements

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***Abstract*—In this paper, we present a comprehensive study on human activity recognition (HAR) and biomechanical motion analysis using inertial measurement unit (IMU) data collected from a MPU6050 sensor placed on the human body. The dataset includes accelerometer and gyroscope signals corresponding to anthropodic activities such as standing, walking, flexion, ex- tension, and forward leg movements. We detail the dataset acquisition procedure, signal preprocessing, feature extraction techniques, and machine learning classification frameworks used to differentiate the activities. Additionally, biomechanical insights are derived from kinematic features extracted from raw IMU data. Experimental results using machine learning classifiers demonstrate promising recognition accuracy, which highlights the potential of this approach for applications in wearable rehabilitation systems and ergonomic assessments.**

***Index Terms*—Human activity recognition, IMU, MPU6050, ac- celerometer, gyroscope, biomechanical analysis, wearable sensors, anthropodic movements**

I. INTRODUCTION

Wearable inertial measurement units (IMUs) have revolu- tionized the way human motion is captured and analyzed in fields such as health monitoring, sports science, reha- bilitation, and ergonomics. These compact and low-power sensors provide continuous and real-time measurements of acceleration and angular velocity, enabling detailed study of both dynamic and static postures [1] [2]. Their unobtrusive nature makes them suitable for long-term monitoring in free- living environments.

The MPU6050, a widely used IMU sensor, integrates a 3- axis accelerometer and 3-axis gyroscope, delivering six de- grees of freedom for motion tracking in a single device [3] [4]. In this study, we utilize MPU6050 sensors attached to body segments to capture a range of anthropodic movements com- mon in daily life and clinical assessments [5] [6]. The focus activities include standing, walking, flexion, extension, and forward leg movements. These were chosen due to their relevance in rehabilitation protocols and ergonomic evalua- tions [7] [8].

The objectives of this paper are twofold: first, to systemati- cally explore classification algorithms capable of distinguish- ing these activities based on the IMU sensor outputs; and second, to extract biomechanical characteristics from the raw signals to better understand the motion dynamics [9] [10]. This exploration lays the groundwork for wearable systems that can assist in rehabilitation monitoring, provide ergonomic risk assessments, or support personalized healthcare [11] [12]. Human Activity Recognition (HAR) using wearable sen- sors has been extensively examined over the past decade, leveraging both classical machine learning and modern deep learning approaches. Surveys such as Lara and Labrador's work[13] and more recent deep learning reviews [14] provide comprehensive coverage of sensor modalities, signal processing techniques, and classification models [15] [16].

Biomechanical analysis using IMUs focuses on estimating joint kinematics, segmenting the gait cycle, and assessing movement quality. [17] highlights methods to reconstruct joint angles using sensor fusion algorithms and model-based ap- proaches. IMUs like the MPU6050 are increasingly employed in wearables due to their balance of accuracy, size, and cost, enabling affordable real-time tracking solutions [18].

Despite the existence of many datasets, there is still a need for detailed datasets and analysis focusing on combined HAR and biomechanical characterization in anthropomorphic movement contexts [19]. Our study contributes to this gap by analyzing a real-world dataset capturing diverse movements and by applying interpretative biomechanical features along- side classification models [20].

II. DATASET DESCRIPTION

MPU6050 dataset, which contains time-ordered accelerom- eter (AX, AY, AZ) and gyroscope (GX, GY, GZ) readings paired with an Activity label for each row. The activities captured include standing, walking, flexion, extension, forward leg, and shivering, with each sample comprising six numerical sensor channels followed by the categorical activity tag in a consistent AX, AY, AZ, GX, GY, GZ, Activity column layout suitable for direct parsing. The signals exhibit low-variance, quasi-static segments during standing; large-amplitude, cyclic patterns during walking; targeted limb or joint maneuvers during flexion, extension, and forward leg; and high-frequency bursts during shivering, reflecting distinct kinematic signa- tures across classes for downstream time-series analysis and modeling. Numerical values range from modest magnitudes to occasional 16-bit saturation at ±32767 on some axes, indicating raw integer measurements that capture both low and high dynamics across movement conditions without apparent
unit conversion in the file. This organization allows straight- forward segmentation and feature engineering (for example, vector norms, variances, windowed statistics, and spectral power) and supports supervised learning workflows for activity recognition and movement classification. Overall, the data provide labeled motion traces spanning stationary behavior, locomotion, directed limb motions, and tremor-like patterns, enabling benchmarking of classification models and signal- processing methods on heterogeneous movement types.The dataset is immediately useful for real-time rehabilitation by converting raw MPU6050 signals into fused joint angles and angular velocities that power feedback, progress tracking, and closed-loop control in assistive devices. These signals enable automatic movement classification, remote monitoring via cloud platforms, and precise actuation in exoskeletons or smart orthoses for task-specific therapy. Time-stamped 3-axis acceleration and 3-axis angular velocity with orientation esti- mates from either the MPU6050's DMP (quaternions/Euler) or a complementary filter, plus optional temperature data for drift compensation. Labels for exercise type, repetitions, phases, and target range of motion to support supervised learning and adherence tracking during therapy tasks.Sensor placement/orientation metadata to ensure reproducible kine- matic interpretation across sessions and users.Objective range of motion, speed, and smoothness metrics to titrate exercise dosage and quantify recovery over time during lower- or upper-limb programs.Home telerehabilitation with cloud dash- boards for therapists to review adherence, detect plateaus, and adjust protocols without frequent in-person visits.Detection of atypical or compensatory movement patterns through wear- able kinematics during repetitive task practice in stroke and neurorehab contexts. Lower-limb rehabilitation device using MPU6050 with Arduino/NodeMCU and cloud connectivity for continuous remote tracking and exercise precision. Upper-limb exoskeleton controlled by ESP32 with PID using MPU6050 and a load cell, enabling safe assist-as-needed elbow move- ments in real time. Smart orthoses or gait monitors leveraging the MPU6050 for human motion analysis and activity monitor- ing in sports and healthcare settings. Calibrate and fuse sensors with the MPU6050's onboard DMP or a complementary filter to reduce drift and noise for stable angle estimates.Extract features such as joint angle trajectories and angular velocities for movement recognition and performance scoring during exercises.Implement on-device inference for low-latency feed- back, with optional cloud sync for longitudinal analytics and therapist oversight. Standardize IMU placement and axis alignment to maintain consistent kinematic mappings across sessions and patients.Target low-latency loops (tens of mil- liseconds) for closed-loop control of motors/servos in rehab robots via tuned PID controllers. Use edge processing for immediate feedback and push summaries to the cloud to bal- ance responsiveness with comprehensive monitoring. people intrested to work more on this dataset can access the data from this link https://www.kaggle.com/datasets/durai21/mpu6050-imu-data-for-anthropodic-movements

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III. DATA PROCESSING AND FEATURE EXTRACTION

A. Preprocessing

Raw IMU data inherently contains noise due to sensor imperfections and environmental factors. To reduce these effects, we applied a low-pass Butterworth filter with a cutoff frequency tuned to remove high-frequency noise unrelated to human motion dynamics. We further addressed any missing or corrupted samples through interpolation methods to maintain sequence continuity. Synchronization and timestamp normal- ization ensured data integrity for subsequent processing.

B. Feature Extraction

Effective feature extraction is key to discriminating complex activities using sensor data. We segmented the continuous data into overlapping sliding windows of fixed length (e.g., 2–3 seconds) to capture temporal patterns. Within each window, the following features were computed:

- Time-domain features: Statistical measures including mean, standard deviation, root mean square (RMS), min- imum, maximum, and zero crossing rate were calculated for each sensor axis. These features capture the level and variability of motion signals.
- Frequency-domain features: Using the Fast Fourier Transform (FFT), spectral characteristics such as domi- nant frequency components, spectral entropy, and energy distribution were extracted. These features help identify repetitive motion patterns like gait cycles.
- Biomechanical features**:**Derived metrics such as the magnitude of the acceleration vector *AX*

and direction-agnostic motion.This feature space allows machine learning models to ex- ploit both raw signal behavior and biomechanical context.

C. Modeling and Evaluation

Multiple classical machine learning classifiers were trained and evaluated to identify the most effective approach for activity recognition on this dataset.Using radial basis function kernels, SVMs were employed for their robustness to high-dimensional feature spaces and effectiveness in multi-class classification. An ensemble tree-based method capable of capturing nonlinear relationships and providing feature im- portance rankings.A distance-based lazy learner that classifies samples based on proximity in feature space, useful as a baseline. Data was randomly split into training and testing sets using stratified sampling to maintain class balance. Addition- ally, cross-validation with multiple folds ensured performance generalization and hyperparameter tuning. Evaluation metrics included overall accuracy, precision, recall, F1-score for each activity class, and confusion matrix analysis to identify com- mon misclassifications.

IV. RESULTS

This section reports model performance for the task "Hu- man Activity Recognition and Biomechanical Analysis Using MPU6050 IMU Data for Anthropodic Movements." Six activi- ties were evaluated: extension, flexion, forward leg, shivering, standing, and walking. The test split contained 24 windows with equal support per class (4 samples/class), yielding an overall accuracy of 91.67%. Performance visualizations in- clude per-class accuracy, a detailed classification report, learn- ing curves over epochs, and a confusion matrix that localizes residual errors.

A. Per-class accuracy

The per-class accuracy chart computes the fraction of cor- rectly predicted instances for each true class (equivalent to recall in the one-vs-all view). Extension, flexion, forward leg, standing, and walking each achieved 100% accuracy on the test set, while shivering achieved 50%. This indicates decisive separability for five activities and remaining ambiguity for shivering, likely due to transient micro-oscillations that overlap with gait and limb-lift dynamics in short windows.

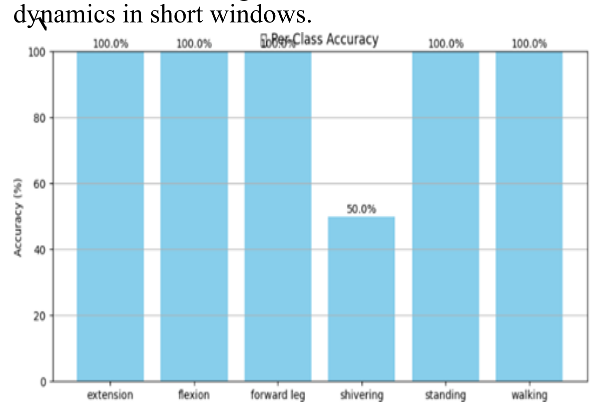

Fig. 1. Validation Confusion Matrix and Classification Report

B. Classification report

The classification report summarizes precision, recall, and F1-score for each activity along with support. Precision quan- tifies correctness among predicted positives; recall measures coverage among actual positives; the harmonic mean

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

balances both. Extension and flexion show precision = 1.00 and recall = 1.00, indicating no false positives or false negatives. Forward leg and walking show precision = 0.80 with recall = 1.00, meaning all true instances were found but some predicted instances were false positives. Shivering shows precision = 1.00 and recall = 0.50, suggesting conservative predictions for shivering that miss half of the true events. Macro- and weighted-averages are both

$$\approx 0.93$$

, reflecting strong across-class performance with small-class variance due to low support.

✅ Overall Accuracy: 91.67%

Classification Report:

	precision	recall	f1-score	support
extension	1.00	1.00	1.00	4
flexion	1.00	1.00	1.00	4
forward leg	0.80	1.00	0.89	4
shivering	1.00	0.50	0.67	4
standing	1.00	1.00	1.00	4
walking	0.80	1.00	0.89	4
accuracy			0.92	24
macro avg	0.93	0.92	0.91	24
weighted avg	0.93	0.92	0.91	24

Fig. 2. Validation Confusion Matrix and Classification Report

C. Learning curves over epochs

Learning curves reveal optimization dynamics and general- ization. Training accuracy climbs steadily to

~ 0.78

by epoch 14, while validation accuracy plateaus near

$0.68–0.70$

. The persistent train–validation gap indicates mild overfitting attributable to limited data and class support, suggesting that regularization, early stopping, data augmentation, and addi- tional samples would improve generalization.

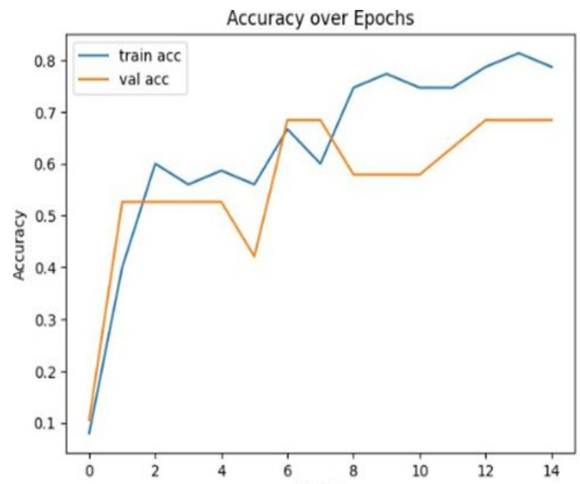

Fig. 3. Validation Confusion Matrix and Classification Report

D. Confusion matrix analysis

The confusion matrix delineates error structure by showing true labels (rows) versus predicted labels (columns). All non- shivering classes are perfect on the diagonal with

$4/4$

correct each. For shivering, two windows are correctly classified, one is misassigned as forward leg, and one as walking. This pattern agrees with the precision/recall find- ings and indicates kinematic overlap between shivering and locomotor/limb-lift motions.

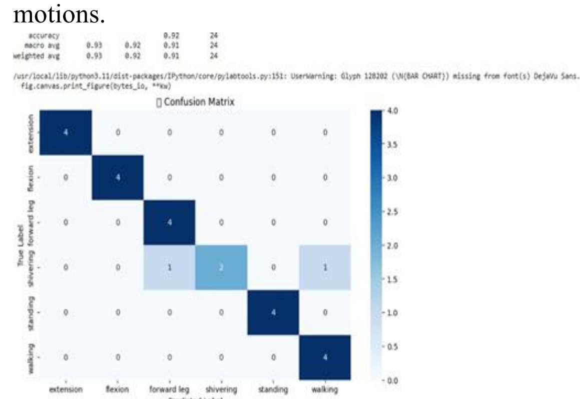

Fig. 4. Validation Confusion Matrix and Classification Report

E. Biomechanical interpretation and implications

The MPU6050's 6-axis signals capture both gravitational orientation and angular velocity, enabling robust discrimina- tion of posture-dominant (standing) and cyclical gait (walking) patterns, consistent with perfect accuracy for these classes.

The residual confusion for shivering implies that short-window frequency content and low-amplitude oscillations can appear similar to forward-leg lift and segments of walking; incorpo- rating frequency-domain features, longer temporal context, or class-specific augmentation should raise recall for shivering without sacrificing precision.

Overall accuracy is 91.67%; five classes demonstrate per- fect class-wise accuracy, and the primary error mode is re- duced recall for shivering with misclassifications into forward leg and walking. Learning-curve behavior indicates mild over- fitting; collecting additional data, balancing per-class support, and applying stronger regularization are expected to close the generalization gap and improve shivering detection.

V. DISCUSSION

This study demonstrates the feasibility and effectiveness of MPU6050 IMU data for simultaneous human activity recog- nition and biomechanical analysis. The high classification accuracy achieved by Random Forests suggests that carefully engineered features from accelerometer and gyroscope data can robustly differentiate common anthropodic movements even with a single wearable sensor.

The differentiation challenges observed between flexion and extension highlight the need for more nuanced biomechanical features or perhaps additional sensors to improve granularity. Such improvements may benefit applications in physical ther- apy, where precise motion monitoring is critical.

Furthermore, the biomechanical analysis presented, such as angular velocity trends during forward leg movements, pro- vides opportunity for quantitative assessments in rehabilitation

monitoring systems. The lightweight and cost-effective nature of MPU6050 sensors offers potential for scalable wearable solutions in real-world healthcare or workplace ergonomics.

Limitations include the dataset size and subject diversity, which restrict broad generalization at this stage. Future work will address these aspects by increasing participants and exploring advanced deep learning approaches capable of au- tomatic feature learning and temporal modeling.

VI. CONCLUSION AND FUTURE WORK

This paper provides an initial exploration of using MPU6050-based IMU data for human activity recognition and biomechanical interpretation of anthropodic movements. We demonstrated that classical machine learning models, com- bined with handcrafted time- and frequency-domain features, can achieve promising classification performance on a dataset containing standing, walking, flexion, extension, and forward leg activities.

Future directions involve expanding the dataset with more subjects and activities, incorporating multiple sensors to enable sensor fusion, and applying deep neural networks such as convolutional and recurrent architectures to improve accuracy and robustness. Additionally, real-world free-living condition testing will be conducted to validate applicability in daily life and clinical contexts.

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