**1. Introduction**

This project applies LSTM-based recurrent neural networks to predict athlete fatigue and injury risk using biomechanical sensor data. By integrating advanced RNN architectures, feature engineering techniques, and robust training practices, our goal is to build a predictive model that not only forecasts fatigue levels but also assesses injury risk with greater accuracy. The work to date has focused on setting up the model architecture, preprocessing the time series data, and conducting initial experiments to validate our approach.

**2. Project Overview and Objectives**

**Primary Objectives:**

* **Deep Learning Application:** Leverage LSTM and bidirectional architectures to capture temporal dependencies in biomechanical signals.
* **Feature Engineering:** Enhance the dataset with novel features such as joint asymmetry metrics, range-of-motion (ROM) deviation scores, and additional temporal energy features.
* **Robust Training and Evaluation:** Incorporate dropout, gradient clipping, and early stopping to ensure a well-generalized model.
* **Multi-task Output:** Extend the model to predict both a continuous fatigue score (regression) and a categorical injury risk (classification).

The project is designed in line with class guidelines by building on established deep learning techniques and incorporating real-world biomechanical data challenges.

**3. Work Accomplished So Far**

**3.1 LSTM Architecture and Code Integration**

* **Baseline and Enhanced Models:**  
  We have implemented a baseline LSTM model using a single LSTM layer with 64 units and MSE loss. Based on early experiments, we have iteratively enhanced the architecture by:
  + Stacking LSTM layers and using a bidirectional wrapper to capture context from both temporal directions.
  + Introducing dropout (p=0.2) for regularization.
  + Incorporating gradient clipping via the Adam optimizer.