

TCN-XLSTM: A HYBRID DEEP TEMPORAL ARCHITECTURE FOR LOWER LIMB JOINT MOMENT ESTIMATION FROM WEARABLE IMU SIGNALS

Author's: Anushiya Shree M1, R. Surendiran2, K. Sujith3, N. Vanjulavalli4

Abstract

The rapid advancement of wearable sensing technologies has enabled continuous and non-invasive monitoring of human movement in real-world environments. Among these technologies, Inertial Measurement Units (IMUs) have emerged as a practical alternative to laboratory-based motion capture systems for biomechanical analysis. However, accurately estimating lower limb joint moments from IMU signals remains a challenging task due to nonlinear dynamics, temporal dependencies, and noise inherent in wearable sensor data. This study proposes TCN-xLSTM, a hybrid temporal deep learning framework that integrates a Temporal Convolutional Network (TCN) with an extended Long Short-Term Memory (xLSTM) architecture for robust lower limb joint moment estimation from multi-channel IMU signals. The proposed model leverages the strengths of both architectures: the TCN component efficiently captures short- to mid-range temporal patterns through dilated causal convolutions and residual connections, enabling multi-scale feature extraction from high-frequency IMU data. In parallel, the xLSTM module enhances long-term temporal modeling by incorporating advanced gating mechanisms that improve memory retention and nonlinear sequence learning. By combining convolutional temporal encoding with enhanced recurrent memory dynamics, the hybrid architecture effectively models complex biomechanical relationships between kinematic inputs and joint kinetics. The framework processes multi-axis accelerometer and gyroscope signals, optionally augmented with orientation-based features, to predict continuous joint moment trajectories for major lower limb joints such as the ankle, knee, and hip across multiple anatomical planes. A sequence-to-sequence regression strategy is employed to generate frame-wise joint moment estimates, ensuring temporal continuity. Additionally, a smoothness-aware loss formulation can be incorporated to preserve biomechanical plausibility in predicted outputs.