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Abstract

Title: Estimation of Ground Reaction Forces in Running via Deep Learning Models: A Comparative Analysis

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Introduction

Ground Reaction Forces (GRFs) are fundamental to the analysis of running biomechanics and play a critical role in performance assessment, injury prevention, and rehabilitation [1]. While GRFs are traditionally measured using expensive and non-portable systems such as instrumented treadmills, there is growing interest in more accessible, scalable alternatives [2]. Inertial Measurement Units (IMUs), which record acceleration, angular velocity, and orientation, have demonstrated potential in this context [3-5]. Recent research has applied deep learning techniques to estimate GRFs from IMU-derived kinematic data [4-6]; however, a standardized benchmark for comparing different models using a publicly available dataset remains absent, limiting reproducibility and cross-study evaluation.

Research Question

This study aimed to develop and compare multiple deep learning models for predicting vertical, anterior, and lateral GRFs using a publicly available dataset. The goal was to provide a reproducible benchmark for GRF estimation from kinematic data, enabling fair comparison across modeling approaches.

Methods

The analysis utilized a publicly available dataset by Fukuchi et al. [7], comprising kinematic and kinetic running data from 28 recreational runners. Each participant completed treadmill running trials at three fixed speeds (2.5 m/s, 3.5 m/s, 4.5 m/s) for 30 seconds per speed. GRFs were recorded via an instrumented treadmill, and kinematic data were captured using a 12-camera motion capture system. Acceleration profiles were computed from the trajectories of reflective markers as performed in [8-9]. Data were partitioned into training (60%), validation (20%), and test (20%) sets by subject. Three model architectures were implemented: a one-dimensional convolutional neural network (1D-CNN), a Long Short-Term Memory network (LSTM), and a hybrid 1D-CNN + LSTM model. Each model was separately optimized for each GRF component, tuning hyperparameters such as number of filters, kernel size, number of layers, number of neurons in the fully-connected layers, presence of batch normalization and/or L2-regularization, batch size, epochs, etc. Leave-One-Subject-Out Cross-Validation (LOSO-CV) was employed for evaluation, with Root Mean Square Error (RMSE) used as the loss function. Some examples of the developed architectures are shown in Figure.

Results

Prediction results for each GRF component were evaluated visually (shown in Figure) and are summarised in Table and compared to the results obtained from analysis on the same dataset [8].

Discussion

All three models demonstrated performance comparable to previous work using simpler artificial neural networks applied to the same dataset.

The findings indicate that complex deep learning models, when properly trained and optimized, can perform competitively for GRF prediction using relatively small biomechanical datasets. However, the study also underscores the limitations imposed by data scarcity, a common challenge in biomechanics.

In this context, model simplicity and careful architectural design may yield more practical and generalizable results than overly complex solutions. These results reinforce the importance of balancing model complexity with dataset size in biomechanical machine learning applications.

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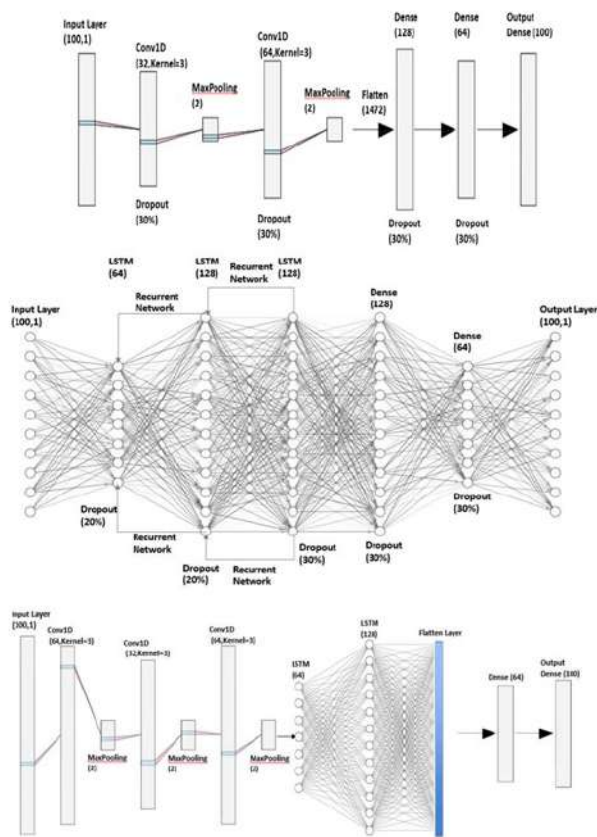


Figure. 1D CNN Model for Vertical Component, LSTM Model for Anterior Component, Hybrid 1D CNN LSTM Model

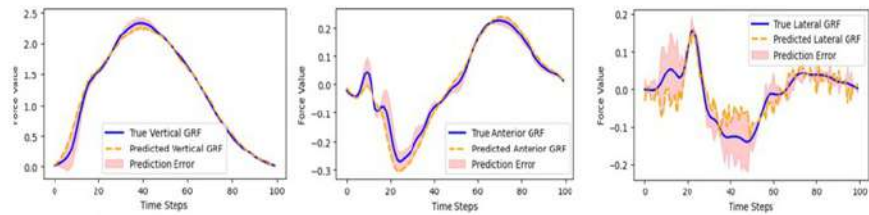


Figure. True vs Predicted GRF plots for Vertical, Anterior and Lateral components from 1D CNN

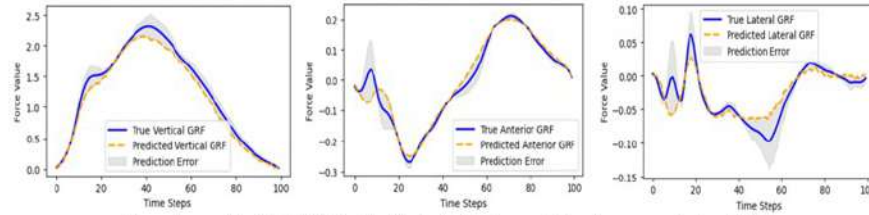


Figure. True vs Predicted GRF plots for Vertical, Anterior and Lateral components from LSTM

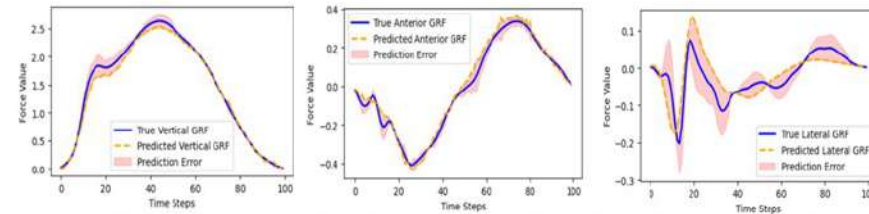


Figure. True vs Predicted GRF plots for Vertical, Anterior and Lateral components from 1D CNN + LSTM

Table. Summary Results

RMSE Test Set (BW)	1D CNN	LSTM	CNN+ LSTM	ANN[8]
Vertical	0.1448±0.05846	0.166±0.0624	0.1402±0.05126	0.134 ± 0.027
Anterior	0.0487±0.0163	0.054±0.0176	0.0464±0.0157	0.041 ± 0.007
Lateral	0.04837±0.02013	0.0526±0.01686	0.0444±0.01546	0.042 ± 0.006