

ANALYSIS OF DEEP LEARNING CLASSIFICATION METHODS OF 3D KINEMATIC DATA FOR NEUROLOGICAL GAIT DISORDERS

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Introduction

Cerebral palsy (CP) is the leading cause of gait disorders in children. 3D clinical gait analysis provides valuable clinical information for guiding therapeutic choices. In a previous work [1], we investigated deep learning (DL) for 3D gait kinematics classification for diagnostic purposes. This work focuses on identifying key features that DL models leverage for classification, enhancing the reliability of the diagnostic tool and comprehension of the gait signal.

Methods

The 3D gait data were collected between 2006 and 2022 at the Brest University Hospital's motion analysis laboratory in France. The dataset included lower limb kinematics from children with unilateral CP (CPu) and from typically developing (TD) children. The data used were pelvic tilt, obliquity, and rotation; hip flexion/extension (F/E), abduction/adduction (Ab/Ad), and internal/external rotation (I/E Rot); knee F/E, Ab/Ad, and I/E Rot; ankle F/E; and foot progression for both legs. Gait signal is represented by a 22 x 101 matrix, comprising the 11 joint angles for each lower limb. For CPu participants, the first side corresponds to the more affected limb, while the second side represents the less affected limb. For TD participants, side selection is randomized.

In this work, we propose employing an iterative feature selection approach to pinpoint the most informative signal components used by three neural networks (ResNet, LSTM and InceptionTime) for gait data classification.

Results

Figure 1 shows for each network, the order of the most informative signals (underlined by color), as well as the associated classification accuracy. Firstly, it is remarkable that by utilizing a single component of the gait signal, high classification accuracy can be attained (higher than 0.92). Secondly, the ankle F/E of the most affected side consistently emerges as the most informative component for all three neural networks, emphasizing its role in gait pattern analysis.

We continued this feature selection strategy to determine the 5 most informative components for each neural network yielding the following results. LSTM: ankle F/E 1, ankle F/E 2, pelvic rotation 1, knee I/E Rot 2, pelvic tilt 1. ResNet: ankle F/E 1, knee Rot I/E 2, ankle F/E 2, pelvic tilt 2, pelvic tilt 1.

InceptionTime: ankle F/E 1, knee Rot I/E 2, hip Ab/Ad 2, knee Ab/Ad 2, hip Ab/Ad 1. 1 and 2 refer to the first and second side.

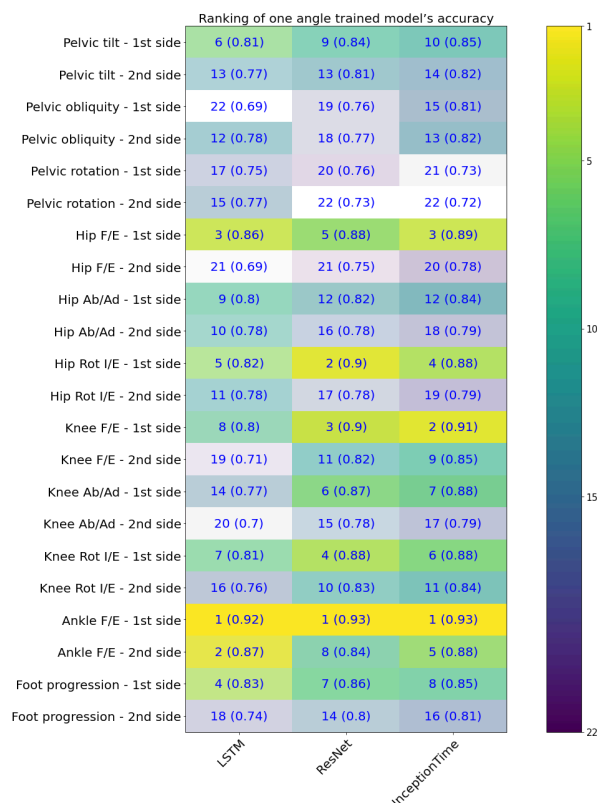


Figure 1: Ranking (from 1 (with the highest accuracy) to 22) and accuracy of one angle trained model.

Discussion

The iterative feature selection method investigated in this work can reveal most informative components of gait signals for classification. By analyzing the angles that consistently achieve the highest accuracy across networks, we can pinpoint the most decisive features that guide the diagnostic process. These key features include both sides of ankle F/E; the first side of hip F/E, hip I/E Rot, and knee F/E. The next step involves integrating these findings with clinical expertise to gain a comprehensive understanding of gait signals.

References

- Zhengyang Lan et al, Computers in Biology and Medicine, 2024

