AUTOMATICALLY DETECTING FATIGUE GAIT BASED ON TIME SERIES BILATERAL PLANTAR FORCE DISTRIBUTION USING DEEP LEARNING ALGORITHMS.

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Introduction:

Fatigue caused by long-distance running may induce alterations of distribution in foot mechanics, which can lead to structural overload. Therefore, the effect of running fatigue on plantar pressure has been more attractive. The risk of fatigue gait has been extensively demonstrated in past studies and is accompanied by changes in bilateral plantar pressure distribution. Early running fatigue detection would help training programs to adjust to prevent the increased risk of overuse injuries. The development of artificial intelligence and machine learning enables human activity recognition to be used effectively for action recognition, risk prediction and condition assessment. Although previous research has made great progress in human movement analysis and load prediction, it has not been sufficient the research in the field of automatic fatigue gait recognition. we decided to choose the Convolutional Long Short-Term Memory Network (ConvLSTM) model recently developed by Shi et al. [1] This model can improve the fully connected structure in the original LSTM model into a convolutional structure while avoiding the loss of spatial and temporal information of plantar pressure. A aim was to perform automatic recognition of fatigue gait using the Convolutional neural network (CNN) and ConvLSTM deep learning models based on data from bilateral time series plantar forces.

Methods

Thirty healthy male amateur runners were recruited from the university and nearby community to participate in our study.

This experiment requires the execution of a running-induced fatigue protocol developed by Koblbauer et al.[2] and 3 times successful tries of dynamic plantar force measurements before and after fatigue using a FootScan pressure plate. A heart rate monitoring band and 15-point Borg scale were applied to monitor and calculate the state of fatigue during the running-induced fatigue protocol. Specific details of the intervention have been described in previous study of Gao et al [3].

the ConvLSTM model improves the fully connected structure in the LSTM model into a convolutional structure (Figure 1). Where i_t, f_t, and o_t are the input gate, oblivion gate, and output gate of the model, respectively. x_t and h_{t-1} are the data input at the current moment and the output of the hidden layer at the previous moment, respectively. c_t is the cell state. The specific operation of CovnLSTM is represented by Equation (1-6).

$$f_t = \sigma\left(W_{xf} * x_t + W_{hf} * h_{t-1} + b_f\right) \quad (1)$$

$$i_t = \sigma(W_{xi} * x_t + W_{hi} * h_{t-1} + b_i) \quad (2)$$

$$\tilde{c}_t = \tanh(W_{xc} * x_t + W_{hc} * h_{t-1} + b_c) \quad (3)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \quad (4)$$

$$o_t = \sigma(W_{xo} * x_t + W_{ho} * h_{t-1} + b_o) \quad (5)$$

$$h_t = o_t \circ \tanh\,(c_t) \quad (6)$$

where $*$ represents the convolution operation and $\circ$ represents the Hadamard product.

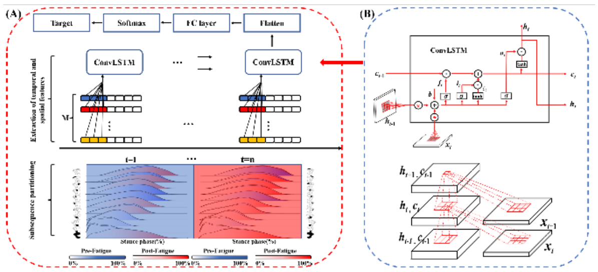

Figure 1: Diagram of the internal structure of ConvLSTM model in this study

Results

Model	Accuracy	Sensitivity	Specificity
CNN	0.800	0.874	0.718
ConvLSTM	0.867	0.874	0.859

Table 1: Classification results of total plantar pressure by different algorithms.

The average accuracy, sensitivity and specificity of the 5 test sets are shown in Table 3. The Accuracy of ConvLSTM is 86.7% greater than CNN (80%). Similarly, the Specificity of ConvLSTM is 85.9% greater than CNN (71.8%). However, sensitivity performed 87.4% in both deep learning models.

Discussion

These findings may provide evidence-based information for the assessment of risk factors for unilateral limb overuse injuries and for the early identification of fatigued gait.

References

1. Shi et al, Advances in neural information processing systems, 28, 2015.
2. Koblbauer et al, J Sci Med Sport, 17:419-424, 2013.
3. Gao et al, Front Physiol, 1792-1804,2022.

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