# A Multichannel-based cuDNNLSTM Deep Learning Model in Walking Speed Classification based on Lower Extremity Kinematics Characteristics

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# **Summary**

Walking speed is a powerful indicator of health events, which are largely due to age, musculoskeletal disorder or other diseases. Comprehensive motion capture system (MCS) is often employed to assess the walking performance based on biomechanical parameters, namely kinetics, kinematics, and electromyography. MCS has posed to high degree of variability within the data representation. Hence, a Multichannel-based- cuDNNLSTM is developed to classify walking speed based on kinematics. This model consists of a 3-Long-Short-Term Memory (LSTM) channel, whereby its output was fused by a Bayes based decision layer. The model was employed to classify the walking speeds from 818 walking cycles. Kinematics were segmented before directed to the input layer. Compared with the standard classification algorithm, the accuracy and F-score attained are 96.65% and 95.42%, respectively. These promising results are essential to be used in clinical settings by the medical practitioners for faster assessment, monitoring and treatment.

## Introduction

MCS demonstrates great potential to be integrated with automated gait analysis. Nonetheless, clinicians whom rely extensively on MCS for diagnosis and treatment have been overwhelmed by numerous complexities such as high data dimensionality, nonlinear data dependencies and nonunique correlations. Therefore, the integration of machine learning (ML) with MCS is a promising solution. ML is the combination of a learning mechanism and computation that is designed particularly for interpreting and processing large volumes of data. ML is capable of producing fast and accurate results. In recent studies, its application has presented new insights into the nature of human gait control through detection, fusion and classification from different multisource data. Recurrent neural networks (RNN) have achieved promising results in sequence modelling tasks, including model complex time-dependent patterns, feature extraction for gait characterization and user recognition. Nonetheless, an ordinary RNN has gradient vanishing issues, preventing it to handle long sequences (Cho et al., 2014). As such, a novel deep learning (DL) model is proposed to overcome the shortcomings of RNN.

## Methods

In this study, the self-selected walking speeds of slow, normal and fast have been collected among the health young adults. For DL development, the complete gait cycles are extracted. The number of gait cycles are reported as such: Slow (296), Normal (299), Fast (282). The collected data are processed for data cleaning, data standardization, data segmentation, data labelling, and data splitting. Thereafter, a novel multichannel integrated cuDNNLSTM model is developed (Figure 1).

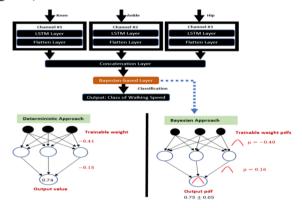


Figure 1: LSTM and cuDNNLSTM Architecture

#### **Results and Discussion**

The results reported from cuDNNLSTM are compared with conventional LSTM. The results are reported in Table 1.

## **Conclusions**

Throughout the study, LSTM based networks were comprehensively analyzed for the classification of slow, normal and fast walking speed using kinematic. The developed cuDNNLSTM has shown better performance than LSTM. Hence, this model could be proposed to assist the medical practitioners and therapists for treatment.

#### References

[1] Aung, H.M.L, et al. (2022). Computation, 10: 127.

Table 1: Interesting data from well-executed experiments. The data have been arranged in an interesting and clear manner.

DL Models	Performance Metrics			
	Accuracy (%)	Sensitivity (%)	Precision (%)	F1-score (%)
LSTM	86.11	83.82	83.20	81.98
cuDNNLSTM	96.65	91.20	91.05	95.42