Lower extremity kinematics walking speed classification using long short-term memory neural frameworks

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Abstract

Walking speed provides a good proxy for gait abnormalities as individuals with medical morbidities tend to walk slower than healthy subjects. The walking speed assessment can be utilized as a powerful predictor of health events, which are related to musculoskeletal disorder and mental disease. The expanding need to distinguish gait pattern of individual according to health status has driven various analytical methods such as observational and instrumented gait analysis methods in capturing the human movement. Significant advances in 3D-gait analysis system have enabled a myriad of studies that advance our understanding of gait biomechanics. However, the data samples obtained from this system are large, with high degrees of variability. Hence, developing a reliable approach to distinguish gait patterns specific to the underlying pathologies is of paramount importance. Through this study, we have proposed the use of a deep learning framework with recurrent neural network (RNN) to interpret human walking speed based on kinematic data, whereby RNN is capable for time series data processing. Nevertheless, this model can hardly learn long-range dependencies across time steps in a sequence due to vanishing gradient. In this study, an improved RNN integrated with NVIDIA CUDA® Deep Neural Network Library Long Short-Term Memory (cuDNN LSTM) is introduced. This model is capable to classify the gait patterns of different walking speeds from seventeen healthy subjects, with a total of 453 gait cycles. Gait kinematic parameters were employed as the input layer of the deep learning architecture based on RNN is integrated with cuDNN LSTM. Our proposed framework has achieved an accuracy of 97% to classify different speeds (slow, normal and fast). This study therefore presents a method towards establishing a powerful tool to translate machine learning for gait analysis into clinical practice, whereby automated classifications of gait pattern could now improve acuity of clinical diagnoses.

Keywords Deep learning · Computational biomechanics · Gait · Kinematics · LSTM

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1 Introduction

The ability to walk is considered as a crucial aspect in order to maintain a good quality of life. Humans perform multitudes of walking speed throughout a day in response to social-cultural factors. Self-chosen gait speed requires the selection of stride length [42], joint angular displacement [22, 57], joint torque and power [8, 45]. However, studies have found that the ability to maintain maximum walking speed reduces with age [27, 65]. Such a condition can be resulted from numerous age-related physiological changes, including joint degeneration [5], muscle weakness [46] and neurological diseases [50]. Furthermore, a few cohort studies have affirmed the association between reduced gait speed with cardiovascular disease [38] and dementia [24]. On the contrary, walking speed, and not age has been considered as the primary determinant of the kinematic and kinetic changes in children and young adult [59, 66]. In light of that, exploration on the knowledge about the effects of gait speed on biomechanical variables is paramount for benefitting clinicians who commonly rely on the outcomes of gait analysis to gauge functional level of patients and to optimize patient care.

In clinical practice, the gait analysis is carried out by clinicians via visual examination [20]. They conduct evaluations on movement patterns of key body segments such as foot, ankle, knee, hip, pelvis and trunk during each phase of cycle [30, 48, 58]. Manual involvement of many segments in a dynamic movement prone to high complexity during clinical assessment. The multiple movements of various segments, which occurred concurrently during a dynamic motion, has resulted in neglections of imperative gait issues during an assessment [7] and observational scales [20, 53]. Several studies and reviews have reported poor reliability with observational gait analysis [7, 49, 51]. Tanikawa et al. estimated poor inter-rater reliability (Cohen's Kappa coefficient 0.1–0.3) even among experienced clinicians [3]. The poor reliability could be attributed to variation in patient state [64], lack of operational definition of gait parameters and insufficient training of the clinicians [62]. As such, observational or bedside gait analysis is of limited value in patient management.

The limitations of the observational method have led to the development of instrumented gait analysis. In this system, a computerized measurement technology is employed to evaluate the rigid segments of a human model [34]. A three-dimensional (3D) pose of the human body is captured in six degrees of freedom (DOF), which three relating to translational and three defining rotational [13]. With the incorporation of body segment inertia parameters, the whole-body centre of mass location can be deduced thus enhance the interpretive power for a kinematic evaluation [55]. Moreover, kinematic and kinetic data can be combined to allow the calculation of joint moments and net joint reaction forces through the inverse dynamics analysis [19]. An increasingly useful application of instrumented gait analysis enables accurate quantification of whole-body pose thus provide clinician with a comprehensive understanding of underlying conditions that affect patient's mobility [61].

With the growth of motion capture system [44, 47, 48, 67] in both visual surveillance and human-machine interface [31], it demonstrates great potential to automate human gait analysis [2, 52, 60]. Different forms of gait biometrics can be obtained based on how the gait information is measured, either via sensor or camera approaches [9, 14, 15]. Various physical factors contributing to human gait, such as height, weight, leg lengths and joint proportions, form one intrinsic pattern of gait characteristic unique to every individual. However, the data representations of the gait tend to be large and contain a high degree of variability [32], making potentially important patterns within the data unrecognisable. To filter these data, it is crucial to develop a data-driven method that can extract the intrinsic and distinguishable gait patterns

from camera or sensor measurement. Studies have suggested that machine learning methods with the attribute to learn and uncover the underlying distribution of data, are well suited for accomplishing this objective [18, 29]. These techniques have long been deployed in the areas of predictive modelling and data mining. Predictive modelling is concerned with finding a function that optimally maps input data to a given output with the goal of making accurate predictions in the unseen data [1]. One example of predictive modelling in biomechanics application is detecting cerebral palsy in children using data from motion capture system, where models are trained to identify children with neuromotor disability based on postural-point features [16]. More recent efforts have centred models for fall detection [26], activity recognition to facilitate out-of-clinic patient monitoring during rehabilitation [36], and event detection to guide interventions such as gait modification [63] and orthopaedic surgery [11]. Data mining, on the other hand, is employed to discover new patterns in the data. Its area of application includes using clustering and classification methods to identify subpopulations that exhibit different types of pathological gait [32].

Machine learning is ubiquitous, impacting many aspects of our life [32]. Recent advances in machine learning have demonstrated remarkable performance in supervised learning tasks, enabling a wide range of applications [54]. Support vector machines (SVM) have been widely employed to detect gait subphases from knee and hip angle parameters based on time-series measurement. A study conducted by Luo et al. used SVM to identify the normal and abnormal gait by detecting the sequence of gait phases [37, 43]. Convolutional neural networks (CNNs), which comprise local feature extraction, weight sharing, and pooling, are employed by various studies [17, 68] to solve the multiclass classification problem, capturing the correlation in temporal data in human motion activities [39] and prediction of gait periods [25]. However, CNN does not capture temporal dependencies [25, 33]. In contrast, recurrent neural network (RNN) has achieved many promising results in sequence modelling tasks such as automatic speech recognition [23, 41], and machine translation [12]. Filtjens et al. has adopted RNN to analyse the inertial signal of Parkinson's patients with freezing of gait [21]. However, an ordinary RNN has gradient vanishing issues, preventing it to handle long sequences [12]. To overcome this limitation, a modified version of RNN has been invented: long short-term memory (LSTM). To overcome this limitation, long short-term memory (LSTM) is developed. With gating mechanisms, LSTM can handle long time dependencies in sequential data [4]. LSTM demonstrated success in classifying gait events in children [35].

The aim of this work is to develop learning methods in advancing automatic analysis of human gait and interpreting human walking speed from a data-driven perspective using kinematic data. For this purpose, we propose an RNN model for supervised classification. The model is trained to capture the temporal dependencies and characteristics of human gait data for classification of walking speed. The presented approach investigates the suitability of understanding and interpreting the classification of gait patterns using state-of-the-art machine learning methods. This project therefore presents a first step towards establishing a powerful tool that can be used as the basis for future application of machine learning in human movement analysis.

2 Methodology

2.1 Subject selection criteria

Seventeen subjects without any neuromuscular impairment, whose age ranges between 20 to 24 years, were selected for this study. Inclusion criteria for the subject selection consist of two requirements: (i) subject must be over 18 years old; and (ii) subject should be representative of an average healthy young adult which did not experience any damage to their bone or muscular structure that currently impacts their ability to walk. All subjects were asked to disclose any known conditions that affected their walking speed for the accuracy of the study. The user profile which contained information such as subject number, height, weight, sex, age, ethnicity, and frequency of physical activity were filled up by the subjects as part of a survey and recorded. They were advised on the procedures and steps involved in the data collection prior to conducting the experiment. The entire data collection process followed the approved protocol granted by the NUS Institutional Review Board (Reference code: B-14-265).

2.2 Data collection

The dynamic performance of the walking speed was conducted at NUS-BME Gait Laboratory, Department of Biomedical Engineering, National University of Singapore. The gait analysis study was performed using the Vicon Motion System ((Vicon MX, Oxford Metrics, UK). This system comprises of eight 100 Hz high-speed cameras, two AMTI force-plates (Watertown, USA), and a data station (Vicon MX Control) where the captured walking trajectories were processed. Anthropometric measurement was acquired for each subject, including the bilateral leg length, ankle and knee width. The reflective markers of 14-mm were placed on the pelvis and lower limb of the subjects according to the biomechanical model of the Vicon Plug-in Gait (Fig. 1).

Before initiating the data collection, calibration was performed on each labelling subject using static trial. This was to help ensure that the markers which were attached on the subject were digitised in the camera view and the segment coordinate systems were defined relative to it. All subjects were requested to perform self-selected slow, normal and fast walking, with 3 trials for each speed, respectively. Subjects were required to be barefooted, and the walking speeds were administered.

The self-selected walking speeds of the subjectss for every trial was characterized, in a post-hoc manner, as slow, normal or fast:

$$\begin{aligned} slow &: \quad 0 < \ v^* \le \bar{v}^*_{normal} - \sigma^*_{normal} \\ normal &: \quad \bar{v}^*_{normal} - \sigma^*_{normal} < v^* \le \bar{v}^*_{normal} + \sigma^*_{normal} \\ fast &: \quad \bar{v}^*_{normal} + \sigma^*_{normal} \ < v^*, \end{aligned}$$

Non-dimensional walking speeds represented by $v^* = v/\sqrt{g\,L_{leg}}$ (v is absolute gait speed; L_{leg} is leg length, and g is gravitational acceleration), $\bar{v}^*_{normal}$ and σ^*_{normal} are the mean and standard deviation, respectively, of the non-dimensional normal comfortable walking speed of the subject group [28, 56].

Once a walking pattern was completely recorded, a 3D trajectory was created to show paths taken by each joint in which the marker was attached. These marker data
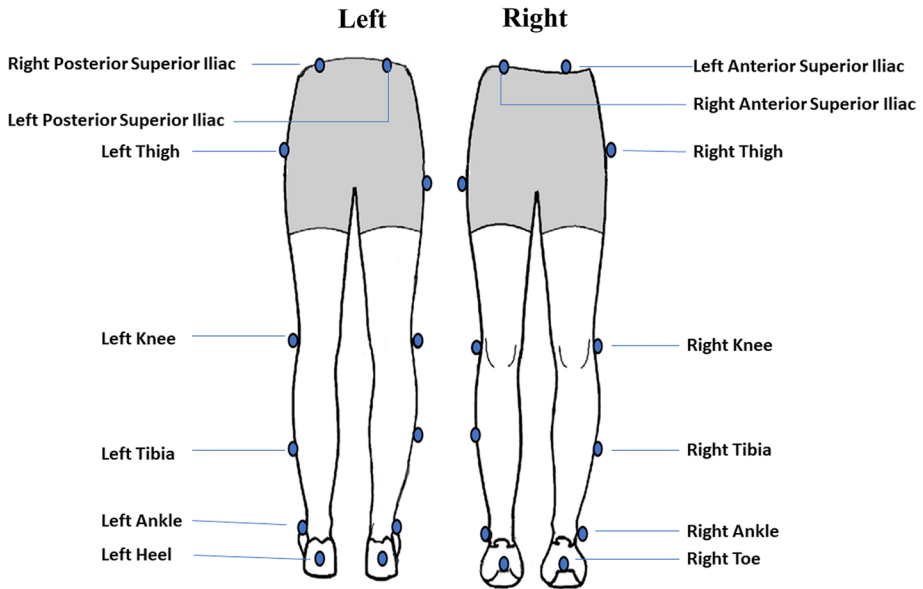
Fig. 1 Marker placement for Plug-In Gait from front (right) and back (left) view

were transformed using rigid-body kinematics into joint angles, which are 3D representations of body movements between segments over time. Followingly, kinematic gait parameters for each walking speed were determined from the synchronized coordinate and force data by using the Vicon Nexus Software.

2.3 Data rearrangement and labelling

There were total of 459 gait cycles collected from the walking trial using Vicon Nexus. However, 6 sets of gait cycles were found to have missing value in the data. The missing data are often a result of occlusion, as markers maybe blocked by body parts or other objects during the tracking process. Also, the motion data can be corrupted by noise for a long period of time. Since the incomplete data can distort the underlying pattern, they were eliminated from this study. The data from the remaining 453 gait cycles consisted of kinematic parameters, which included the ankle, hip and knee angles from sagittal, frontal and transverse planes (Fig. 2). These parameters were employed as cores to differentiate the gait speed in our proposed neural network training. Prior to train the of machine learning model, data labelling was performed on each set of gait cycle. Categorical encoding was employed to convert the categorical data ("Speed") into numerical form such that "Slow" = 0, "Normal" = 1, and "Fast" = 2. Information on gait data used in the experiment is summarized in Table 1.

Notably, 48,253 observations have been collected from the abovementioned 453 gait cycles using the high infrared cameras. To evaluate the classification performance, data sets for training and testing were constructed based on 80:20 ratio.

X_AnkleAngles	Y_AnkleAngles	Z_AnkleAngles	X_HipAngles	Y_HipAngles	Z_HipAngles	X_KneeAngles	Y_KneeAngles	Z_KneeAngles	Speed
-17.57790	5.430290	-28.32940	-0.633072	-5.165960	26.33210	49.70080	27.41160	6.726230	Normal
-9.21136	2.341410	-22.92050	7.636360	-3.459020	24.39980	54.57340	21.96460	3.356960	Slow
4.88287	4.408100	-25.53540	8.593380	9.052960	26.74460	3.30173	4.08138	-0.834656	Slow
5.57431	1.252190	-8.71744	-3.733000	-0.488170	1.22320	36.85030	-3.57215	9.755370	Normal
7.77613	6.023270	-32.99450	21.082900	-2.264500	33.64080	53.66210	27.70610	13.531600	Slow
-1.31134	4.760390	-20.11280	20.549200	-6.253660	7.42592	58.16800	14.18270	-0.414042	Normal
1.40652	2.931200	-25.03130	15.212900	-7.795800	18.63680	67.80630	17.94470	10.522100	Fast
7.51012	0.397278	-3.23425	4.242650	-1.821240	6.99637	10.04570	2.43932	-18.640600	Normal
13.28140	0.705038	-6.67770	-14.033800	0.363068	7.27605	7.94142	3.44039	-4.327960	Slow
-4.22528	1.374290	-14.32960	28.553900	-2.456150	8.91335	21.47460	6.25107	-9.849250	Normal

Fig. 2 Overview of gait datasets

Table 1 Gait cycles for various walking speeds

Categories	Numerical Representative	Amount of gait cycles
Slow	0	151
Normal	1	155
Fast	2	147

Fig. 3 A simple recurrent neural network with an input layer (*x*), hidden state (*h*) and output (*o*) at timestep *t*. The hidden step, h, is served as the memory of the network and calculated based on the previous hidden state and the input of current step
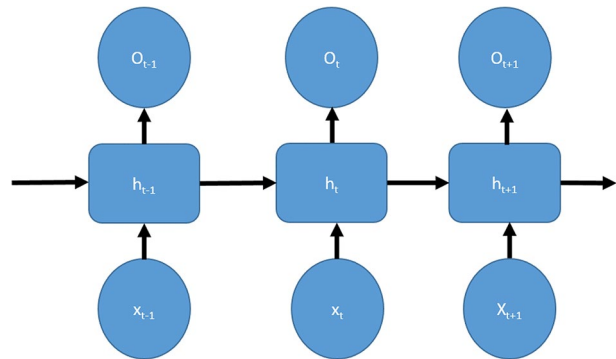
2.4 Deep learning framework development and validation

The neural networks were trained using Keras and TensorFlow as its backend, with Google Colab on free Tesla K80 GPU. A motion capture system provides time-series of measurement of human gait. Therefore, RNN is adopted to capture the sequential relationship in the acquired kinematic data. A RNN is a neural network architecture for handling sequential data (e.g., time series). It consists of feedback connections between each of its units, allowing the network to link all prior inputs to its outputs (Fig. 3). While in principle RNN is a powerful model, it can hardly handle a very long sequence. Among the main reason why this model is so unwieldy are the vanishing gradient and exploding gradient problems described in Bengio et al. [6]. Compared to classical machine learning, a Long Short-Term Memory (LSTM) network can handle raw data directly and does not require hand-crafted feature extraction from time series. An illustration of a LSTM is illustrated in Fig. 4. The cells contain gates and self-loop
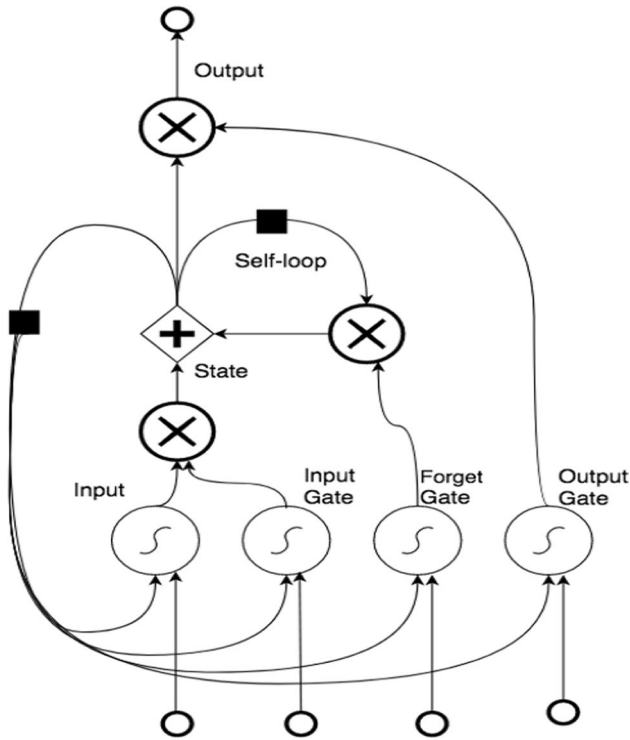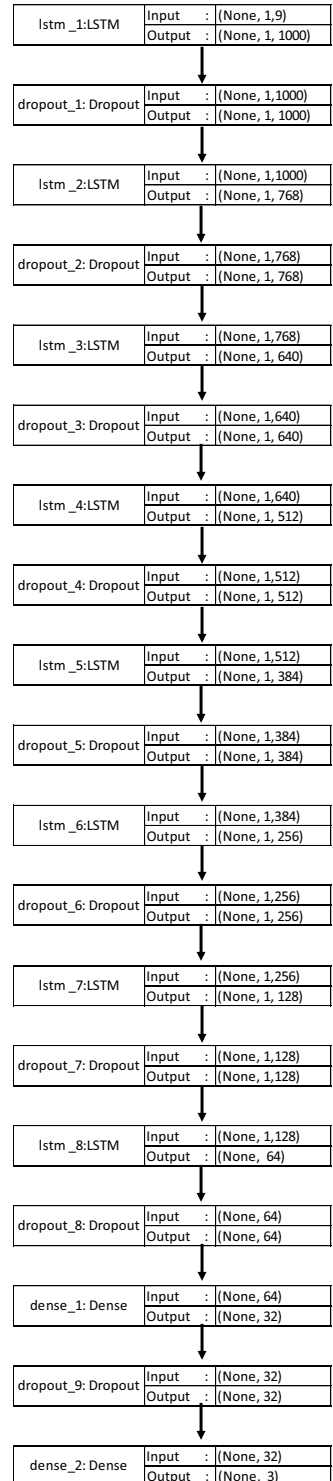
Fig. 4 A block diagram of LSTM memory cell. There are three major components in an LSTM network: the input gate, the forget gate and the output gate. These gates contain a nonlinear activation function which is sigmoid. The input gate would decide the amount of information to be added to the cell state. A forget gate determines how much of the previous internal state to remember. Meanwhile, the output gate controls the information to the output based on the cell state

to generate path where the gradient can flow for long durations. To capture long-term dependencies in a sequence, an improved recurrent network (RNN) integrated with cuDNN LSTM (NVIDIA CUDA® Deep Neural Network Library Long Short-Term Memory) were introduced in this study. Noted that the cuDNN LSTM was proven to be about 2 to 2.8 times faster in contrast to the standalone LSTM model [17]. Therefore, it is beneficial for long sequence data as the taken to train is significantly reduced.

In this study, the proposed model consisted of 6 CuDNN LSTM layers of sizes 768, 640, 512, 384, 256 and 128, followed by a dense layer of size 32, and an output layer of size 3 (Fig. 5). The network employed a batch size of 1000 with the Adam optimizer to run for 2000 epochs. A learning rate of 0.0001 was set as the default parameter. To prevent the training data from overfitting, a dropout of 0.2 was applied to all CuDNN LSTM layers. The rectified linear unit (ReLU) was adopted in the densely connected layer as non-linear activation function. In the output layer, a softmax activation function was employed to calculate the probabilities of each walking speed over the studied speed classes. The developed model was validated by making predictions of different gait speeds from testing data (20%). Subsequently, the prediction accuracy is reported.

Fig. 5 The architecture of the proposed deep learning neural framework

lstm _1:LSTM	Input :	(None, 1,9)
	Output :	(None, 1, 1000)

dropout_1: Dropout	Input :	(None, 1,1000)
	Output :	(None, 1, 1000)

lstm _2:LSTM	Input :	(None, 1,1000)
	Output :	(None, 1, 768)

dropout_2: Dropout	Input :	(None, 1,768)
	Output :	(None, 1, 768)

lstm _3:LSTM	Input :	(None, 1,768)
	Output :	(None, 1, 640)

dropout_3: Dropout	Input :	(None, 1,640)
	Output :	(None, 1, 640)

lstm _4:LSTM	Input :	(None, 1,640)
	Output :	(None, 1, 512)

dropout_4: Dropout	Input :	(None, 1,512)
	Output :	(None, 1, 512)

lstm _5:LSTM	Input :	(None, 1,512)
	Output :	(None, 1, 384)

dropout_5: Dropout	Input :	(None, 1,384)
	Output :	(None, 1, 384)

lstm _6:LSTM	Input :	(None, 1,384)
	Output :	(None, 1, 256)

dropout_6: Dropout	Input :	(None, 1,256)
	Output :	(None, 1, 256)

lstm _7:LSTM	Input :	(None, 1,256)
	Output :	(None, 1, 128)

dropout_7: Dropout	Input :	(None, 1,128)
	Output :	(None, 1,128)

lstm _8:LSTM	Input :	(None, 1,128)
	Output :	(None, 64)

dropout_8: Dropout	Input :	(None, 64)
	Output :	(None, 64)

dense_1: Dense	Input :	(None, 64)
	Output :	(None, 32)

dropout_9: Dropout	Input :	(None, 32)
	Output :	(None, 32)

dense_2: Dense	Input :	(None, 32)
	Output :	(None, 3)

3 Result and discussion

3.1 Classification performance of RNN integrated with cuDNN-LSTM deep learning framework

We train our proposed neural network to estimate the walking speeds based on the kinematic lower limb joint data, which were calculated using motion capture analysis software, Nexus (VICON). Our model took 2 h and 46 min to complete the training. To analyse the classification performance, both loss and accuracy metrics have been evaluated and visualized. A loss function provides an estimate of loss that the classifier incurs as a result of disagreement between the predicted label and true label in the training data. We select sparse categorical cross entropy in our study to update the weights by backpropagating the error backward. Followingly, back-propagation is used to reduce the loss function's value with regard to the model's parameters by changing the weight vector values through an optimization algorithm known as Adaptive Moment Estimation (Adam) in this model. An accuracy function, meanwhile, refers to the proportion of correct predictions for the test data, and is assessed across epochs to ensure stability. The visualization provides an interpretable way to determine which model is best at identifying the relationships between the kinematic variables based on the training data. To review the performance metrics during the training of our proposed deep learning model, graphs of accuracy and loss on the training and test datasets over 2000 epochs are illustrated in Fig. 6.

As showed in the Fig. 6, the training epochs for training data are represented by red lines and blue for test data. Both plots show good convergence of the model across epochs with regard to loss and classification accuracy. From Fig. 6a, the accuracy is found to be increased drastically at around 300th epochs and the increment is slowing down after this point. With 2000 epochs, the percentage for both training and test increases to 98.7% and 97.3%, respectively and does not show an increase in accuracy with higher iterations. Therefore, 2000 epochs are considered as the ideal value for the training epochs of this model. In Fig. 6b, the plot of test loss decreases to a point of stability and has a small gap with the training loss. Therefore, it can be deduced that a good fit is achieved in our model. The test and training loss stop at 1800th and 1900th epochs, respectively.

The proposed deep learning model was then used to perform a prediction on the walking speed of certain gait data chosen from the test sample. The classifier was run to classify 20% of the test samples to assess the prediction confidence. The results showed that the built model has an average accuracy of 97.5% for a total of 20 predictions made (Table 2).
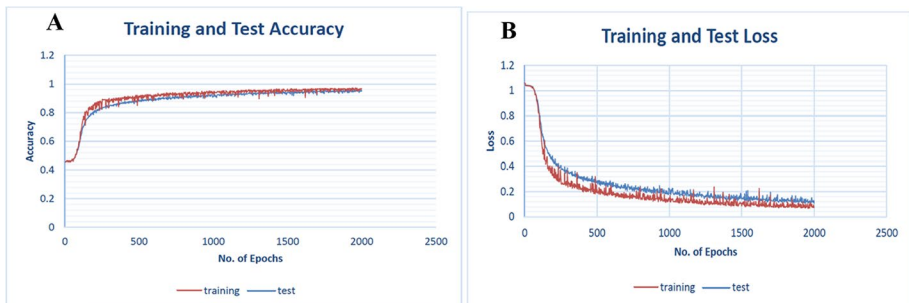

Fig. 6 The classifier's training and test for (**A**) Accuracy and (**B**) Loss

Sequence no. of test data	Prediction	Prediction Confidence (%)	Ground Truth
5	Slow	82.6	Slow
10	Normal	96.2	Normal
15	Fast	100	Fast
20	Normal	100	Normal
25	Slow	100	Slow
30	Normal	100	Normal
35	Slow	84.2	Slow
40	Slow	99.9	Slow
45	Normal	98.4	Normal
50	Slow	100	Slow
55	Slow	100	Slow
60	Normal	100	Normal
65	Slow	99.8	Slow
70	Slow	100	Slow
75	Slow	89.7	Slow
80	Normal	99.9	Normal
85	Normal	100	Normal
90	Slow	99.8	Slow
95	Slow	99.5	Slow
100	Slow	100	Slow

Table 2 Validation of deep learning model

A confusion matrix was computed to visualize the overall classification results (Fig. 7). The off-diagonal element is ranged from 0.01 to 0.02, thus indicate low misclassification. Therefore, we can deduce that the model built of CuDNN LSTM is promising to evaluate and train the sequential data to evaluate the walking cycle as it able to capture the long dependencies of the gait data and produce the mapping of sequence from past observations to walking speed.

3.2 Correlation coefficient between walking speed and kinematic parameters

Aforementioned, the test accuracy of 97.3% has shown the relationship between gait speeds with the joint angles from different planes. To understand the correlation between the mentioned parameters with walking speed, a standard correlation between every pair of attributes has been computed. The results are showed in Table 3. From Fig. 8, we observe an increasing trend in amplitude of the signal with respect to the walking speed from slow to fast, this signifies a positive correlation, which is consistent with the outcomes shown in Table 3.

From Table 3, the knee flexion angles from sagittal, transverse, and frontal plane showed the largest sensitivity to walking speed. Meanwhile, the ankle plantarflexion angle at sagittal and transverse plane had a lower correlation with walking speed across the joint levels. Such a condition can be explained through the visual representation of plane joint angles throughout the gait cycle at knee, hip and ankle in Fig. 8.
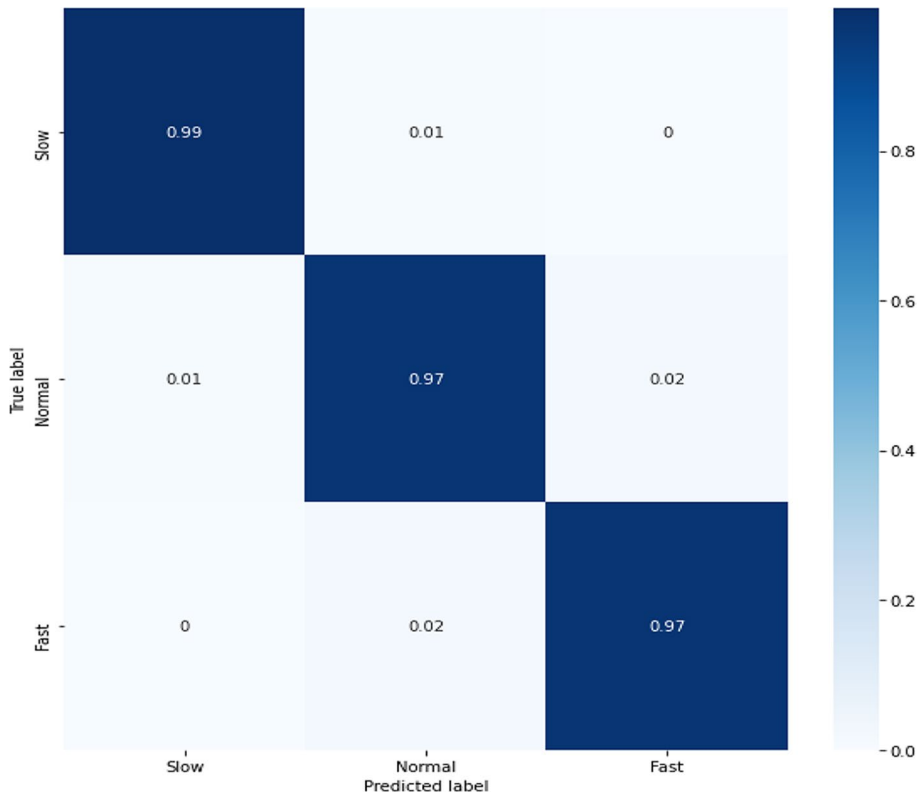
Fig. 7 Confusion matrix of CuDNNLSTM model in gait datasets

Table 3 Correlation between each attribute with walking speed	Parameters	Standard Correlation Coefficient
	Knee Angles (sagittal)	0.131001
	Knee Angles (transverse)	0.115717
	Knee Angles (frontal)	0.074566
	Ankle Angles (frontal)	0.060541
	Hip Angles (frontal)	0.030683
	Hip Angles (transverse)	0.014892
	Hip Angles (sagittal)	−0.002577
	Ankle Angles (sagittal)	−0.005358
	Ankle Angles (transverse)	−0.091204

From Fig. 8, as walking speed increases, so does the peak joint angles across the knee regardless of anatomical planes. The result matches with the previous research conducted by Mentiplay et al. [40]. Generally, at the beginning of the swing phase, the foot goes from plantar flexion to dorsal flexion. As the knee joint is a hinge type, it allows flexion and
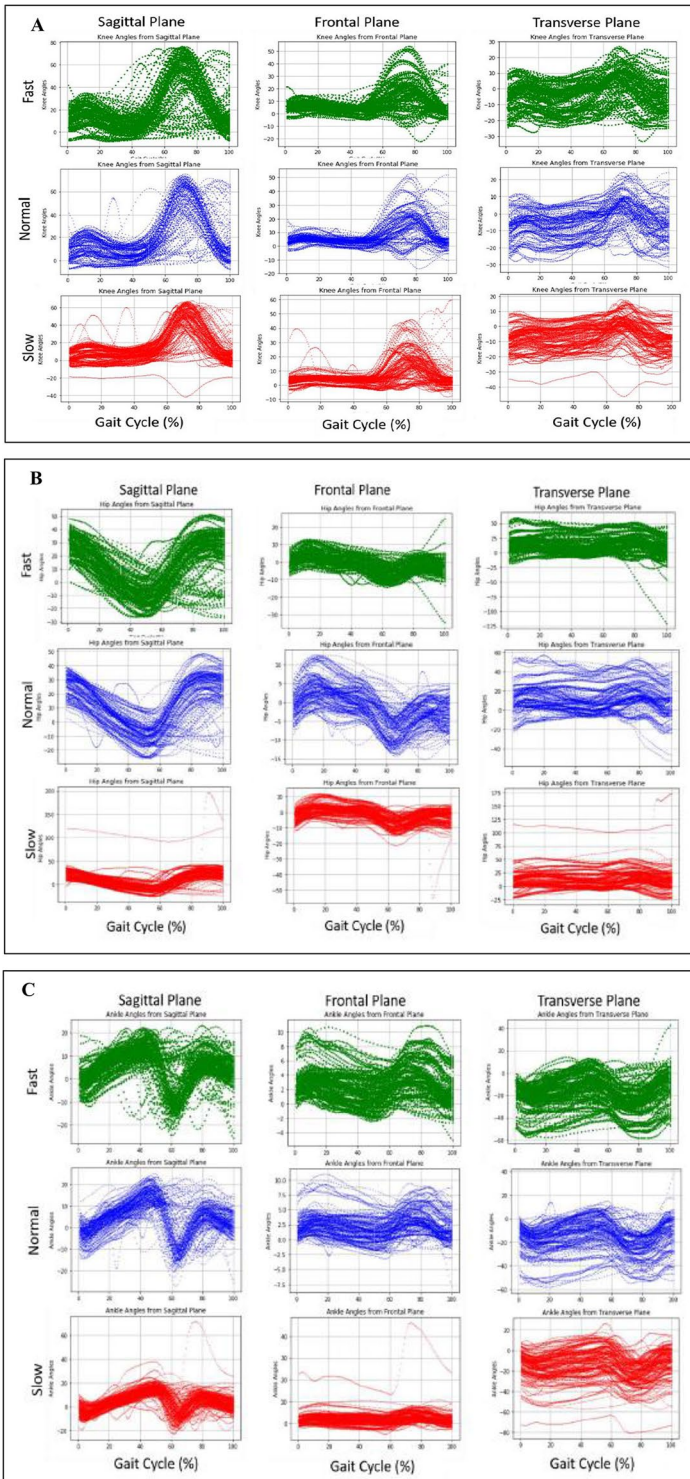
◀ **Fig. 8** **A** Knee, **B** Hip and **C** Ankle angles for slow, normal and fast walking speed at sagittal, frontal and transverse planes

extension, with a small amount of rotation and gliding motions [10]. The hips move from extension to flexion, and the pelvis rotates and changes its tilt. An increasing tilt of the trunk in the direction of progression brings the centre of mass of body forward and assist in increasing rate of movement. For a fast-walking speed, higher power will be generated at the knee joint to achieve a longer ambulated distance. Therefore, a higher flexion peak at the knee can be observed across the sagittal, frontal, and transverse planes. The force transferred to the ankle joint will compensate for forward and backward displacement of the body's center of gravity in order to stabilize the foot and propel the limb forward. Thus, correlation of coefficient for ankle angle at sagittal plane (refer Table 3) is low and the ankle angles at sagittal plane as showed in the Fig. 8c is consistent across slow, normal and fast walking gait. Although the ankle joint is uniaxial, the axis is oblique, therefore the movement in transverse is less significant during the walking gait.

4 Conclusion

In this paper, we proposed a method for classifying walking for various speeds by extracting features based on a RNN integrated with cuDNN LSTM network. The training and testing accuracy of our proposed method were 97.5% and 97.3%, respectively. Despite the high accuracy, there are some limitations reported in this study. Firstly, only young and healthy subjects were recruited in this study, hence our kinematics findings may not be applicable to older adults. In addition, due to the stride interval varies in each subject, the average stride times of the subjects were not employed as the input of our proposed model. Such a condition might cause the sample to be nonrepresentative in the training data, thus affecting the accuracy of the model. Therefore, the average gait data of all subjects should be taken into consideration for higher accuracy and precision for future work. Besides, expanding the data can help improve the generalization and reduce the variability in the models. Noted that the study conducted by Mentiplay et al. [40] has highlighted that gait speed will affect the amplitude of spatiotemporal gait parameters, joint kinematics, joint kinetics and ground reaction forces with a decrease at slow speeds and increase at fast speed in relation to the comfortable speed. Considering that, kinetic parameters such as ground reaction force need to be employed concurrently with kinematic parameters as the determinant of gait pattern in different age populations for future study.

References

1. Aertbelien E, De Schutter J (2014) Learning a predictive model of human gaitfor the control of a lower-limb exoskeleton. In 5th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics. IEEE, pp 520–525

2. Akhtaruzzaman MD, Shafie AA, Khan MR (2016) Gait analysis: systems, technologies, and importance. J Mech Med Biol 16(07):1630003

3. Alexander NB et al (2003) Oxygen-uptake (VO2) kinetics and functional mobility performance in impaired older adults. J Geronotolo: Med Sci 8:734–739

4. Azzouni A, Pujolle G (2017) A long short-term memory recurrent neural network framework for network traffic matrix prediction. ArXiv. abs/1705.05690.

5. Baker R (2006) Gait analysis methods in rehabilitation. J Neuroeng Rehabil 3:4

6. Bengio Y, Frasconi P, Simard P (1993) The problem of learning long-term dependencies in recurrent networks. In: IEEE International Conference on Neural Networks

7. Brunnekreef JJ et al (2005) Reliability of videotaped observational gait analysis in patients with orthopedic impairments. BMC Musculoskelet Disord 6:17

8. Burnfield JM et al (2000) The influence of lower extremity joint torque on gait characteristics in elderly men. Arch Phys Med Rehabil 81(9):1153–1157

9. Ceseracciu E, Sawacha Z, Cobelli C (2014) Comparison of markerless and marker-based motion capture technologies through simultaneous data collection during gait: proof of concept. PLoS One 9(3):e87640

10. Chan CW, Rudins A (1994) Foot biomechanics during walking and running. Mayo Clin Proc 69(5):448–461

11. Chia K et al (2017) The challenge of using statistical models to predict gait outcomes of orthopaedic surgery. Gait Posture 57:141–142

12. Cho K, et al. (2014) Learning phrase representations using RNN encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078

13. Collins TD et al (2009) A six degrees-of-freedom marker set for gait analysis: repeatability and comparison with a modified Helen Hayes set. Gait Posture 30(2):173–180

14. Colyer SL et al (2018) A review of the evolution of vision-based motion analysis and the integration of advanced computer vision methods towards developing a Markerless system. Sports Med Open 4(1):24

15. Corazza S et al (2006) A markerless motion capture system to study musculoskeletal biomechanics: visual hull and simulated annealing approach. Ann Biomed Eng 34(6):1019–1029

16. Cunningham R et al (2019) Fully automated image-based estimation of postural point-features in children with cerebral palsy using deep learning. R Soc Open Sci 6(11):191011

17. Dorschky E et al (2020) CNN-based estimation of sagittal plane walking and running biomechanics from measured and simulated inertial sensor data. Front Bioeng Biotechnol 8:604

18. Machine vision gait-based biometric cryptosystem using a fuzzy commitment scheme. Journal of King Saud University-Computer and Information Sciences 34(2):204–217

19. Faber H, van Soest AJ, Kistemaker DA (2018) Inverse dynamics of mechanical multibody systems: an improved algorithm that ensures consistency between kinematics and external forces. PLoS One 13(9):e0204575

20. Ferrarello F et al (2013) Tools for observational gait analysis in patients with stroke: a systematic review. Phys Ther 93(12):1673–1685

21. Filtjens B et al (2020) A data-driven approach for detecting gait events during turning in people with Parkinson's disease and freezing of gait. Gait Posture 80:130–136

22. Granata KP, Abel MF, Damiano DL (2000) Joint angular velocity in spastic gait and the influence of muscle-tendon lengthening. J Bone Joint Surg Am 82(2):174–186

23. Graves A, Mohamed, Hinton G (2013) Speech recognition with deep recurrent neural networks. In: 2013 IEEE International Conference on Acoustics, Speech and Signal Processing

24. Hackett RA et al (2018) Walking speed, cognitive function, and dementia risk in the English longitudinal study of ageing. J Am Geriatr Soc 66(9):1670–1675

25. Hawas AR et al (2019) Gait identification by convolutional neural networks and optical flow. Multimed Tools Appl 78(18):25873–25888

26. Hemmatpour M et al (2019) A review on fall prediction and prevention system for personal devices: evaluation and experimental results. Adv Hum-Comput Interact 2019:1–12

27. Himann JE et al (1988) Age-related changes in speed of walking. Med Sci Sports Exerc 20(2):161–166

28. Hof AL et al (2002) Speed dependence of averaged EMG profiles in walking. Gait Posture 16:78–86

29. Horst F et al (2019) Explaining the unique nature of individual gait patterns with deep learning. Sci Rep 9(1):2391

30. Huang WW, VanSwearingen J (2019) An observational treatment-based gait pattern classification method for targeting interventions for older adult males with mobility problems: validity based on movement control and biomechanical factors. Gait Posture 71:192–197

31. Ivanov A, Skripnik T (2019) Human-Machine Interface with Motion Capture System for Prosthetic Control. In 2019 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus) IEEE, pp 235–239
32. James EM, Issa T, Issac W (2015) Machine learning techniques for gait biometric recognition using the ground reaction force. Switzerland, SpringerNature
33. Karatsidis A, et al. (2018) Predicting kinetics using musculoskeletal modeling and inertial motion capture. arXiv preprint arXiv:1801.01668
34. Lee G, Pollo FE (2001) Technology overview. J Clin Eng 26(2):129–135
35. Lempereur M et al (2020) A new deep learning-based method for the detection of gait events in children with gait disorders: proof-of-concept and concurrent validity. J Biomech 98:109490
36. Loya A, Deshpande S, Purwar A (2020) Machine learning-driven individualized gait rehabilitation: classification, prediction, and mechanism design. Journalof Engineering and Science in Medical Diagnostics and Therapy 3(2):021105
37. Luo J, Tang J, Xiao X (2016) Abnormal gait behavior detection for elderly based on enhanced Wigner-Ville analysis and cloud incremental SVM learning. J Sensors 2016:1–18
38. Marino FR et al (2019) Gait speed and mood, cognition, and quality of life in older adults with atrial fibrillation. J Am Heart Assoc 8(22):e013212
39. Martinez-Hernandez U, Solis AR, Dehghani-Sanij A (2018) Recognition of Walking Activity and Prediction of Gait Periods with a CNN and First-Order MC Strategy 897–902
40. Mentiplay BF et al (2018) Lower limb angular velocity during walking at various speeds. Gait Posture 65:190–196
41. Miao Y, Gowayyed M, Metze F (2015) EESEN: End-to-end speech recognition using deep RNN models and WFST-based decoding. In: 2015 IEEE Workshop on Automatic Speech Recognition and Understanding (ASRU)
42. Miller ME et al (2018) Gait speed and mobility disability: revisiting meaningful levels in diverse clinical populations. J Am Geriatr Soc 66(5):954–961
43. Moraes R, Valiati JF, Gavião Neto WP (2013) Document-level sentiment classification: an empirical comparison between SVM and ANN. Expert Syst Appl 40(2):621–633
44. Mundermann L, Corazza S, Andriacchi TP (2006) The evolution of methods for the capture of human movement leading to markerless motion capture for biomechanical applications. J Neuroeng Rehabil 3:6
45. Neckel ND et al (2008) Abnormal joint torque patterns exhibited by chronic stroke subjects while walking with a prescribed physiological gait pattern. J NeuroEng Rehabil 5(1):19
46. Neptune RR, McGowan CP (2016) Muscle contributions to frontal plane angular momentum during walking. J Biomech 49(13):2975–2981
47. Norris M, Anderson R, Kenny IC (2013) Method analysis of accelerometers and gyroscopes in running gait: a systematic review. Proc Inst Mech Eng Part P: J Sports Eng Technol 228(1):3–15
48. Payne C (2002) Methods of Analysing gait. In: Linda M, Warren T (eds) Assessment of lower limb. Churchill Livingstone, China, pp 304–319
49. Pusara A et al (2019) Reliability of a low-cost webcam recording system for three-dimensional lower limb gait analysis. Int Biomech 6(1):85–92
50. Rasmussen LJH et al (2019) Association of Neurocognitive and Physical Function with Gait Speed in midlife. JAMA Netw Open 2(10):e1913123
51. Rathinam C et al (2014) Observational gait assessment tools in paediatrics--a systematic review. Gait Posture 40(2):279–285
52. Redkar S (2017) A review on wearable inertial tracking based human gait analysis and control strategies of lower-limb exoskeletons. Int Robot Autom J 3(7):00080
53. Ridao-Fernandez C, Pinero-Pinto E, Chamorro-Moriana G (2019) Observational gait assessment scales in patients with walking disorders: systematic review. Biomed Res Int 2019:2085039
54. Schmidhuber J (2015) Deep learning in neural networks: an overview. Neural Netw 61:85–117
55. Schulein S et al (2017) Instrumented gait analysis: a measure of gait improvement by a wheeled walker in hospitalized geriatric patients. J Neuroeng Rehabil 14(1):18
56. Schwartz MH, Rozumalski A, Trost JP (2008) The effect of walking speed on the gait of typically developing children. J Biomech 41:1639–1650
57. Shemmell J et al (2007) Control of interjoint coordination during the swing phase of normal gait at different speeds. J NeuroEng Rehabil 4(1):10
58. Soubra R, Chkeir A, Novella JL (2019) A systematic review of thirty-one assessment tests to evaluate mobility in older adults. Biomed Res Int 2019:1354362
59. Stansfield BW et al (2001) Normalized speed, not age, characterizes ground reaction force patterns in 5-to 12-year-old children walking at self-selected speeds. J Pediatr Orthop 21(3):395–402

60. Stief F (2018) Variations of marker sets and models for standard gait analysis. In: Müller B, Wolf S (eds) Handbook of human motion. Springer, Cham, pp 509–526

61. Topley M, Richards JG (2020) A comparison of currently available optoelectronic motion capture systems. J Biomech 106:109820

62. Toro B, Nester CJ, Farren PC (2003) The status of gait assessment among physiotherapists in the united Kingdom11No commercial party having a direct financial interest in the results of the research supporting this article has or will confer a benefit upon the authors(s) or upon any organization with which the author(s) is/are associated. Arch Phys Med Rehabil 84(12):1878–1884

63. Turner A, Hayes S (2019) The classification of minor gait alterations using wearable sensors and deep learning. IEEE Trans Biomed Eng 66(11):3136–3145

64. Venkataraman K et al (2020) Teleassessment of gait and gait aids: validity and interrater reliability. Phys Ther 100(4):708–717

65. Weber D (2016) Differences in physical aging measured by walking speed: evidence from the English longitudinal study of ageing. BMC Geriatr 16:31

66. Wren TAL et al (2011) Efficacy of clinical gait analysis: a systematic review. Gait Posture 34(2):149–153

67. Zeng H, Zhao Y (2011) Sensing movement: microsensors for body motion measurement. Sensors (Basel) 11(1):638–660

68. Zhang Y et al (2019) A comprehensive study on gait biometrics using a joint CNN-based method. Pattern Recogn 93:228–236

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