Computers in Biology and Medicine 106 (2019) 33–39

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/compbiomed

Application of supervised machine learning algorithms in the classification of sagittal gait patterns of cerebral palsy children with spastic diplegia

Yanxin Zhang[a,*], Ye Ma[b]

[a] Department of Exercise Sciences, Faculty of Science, The University of Auckland, New Zealand
[b] The Research Academy of Grand Health, Faculty of Sport Science, Ningbo University, China

ARTICLE INFO

Keywords:
Gait classification
Supervised machine learning
Gait analysis
Artificial neural network
Decision tree

ABSTRACT

Gait classification has been widely used for children with cerebral palsy (CP) to assist with clinical decision making and to evaluate different treatment outcomes. The aim of this study was to evaluate supervised machine learning algorithms in the classification of sagittal gait patterns for CP children with spastic diplegia. Gait parameters were extracted from gait data obtained from two hundred children with spastic diplegia CP, and were used to represent the key kinematic features of each individual's gait. Seven supervised machine learning algorithms including an artificial neural network (ANN), discriminant analysis, naive Bayes, decision tree, *k*-nearest neighbors (KNN), support vector machine (SVM), and random forest were compared by constructing a gait classification system based on the same gait data. The performance of these algorithms was then evaluated using a standard 10-fold cross-validation procedure. The results show that the ANN has the best prediction accuracy (93.5%) with a low resubstitution error (5.8%), high specificity (> 0.93) and high sensitivity (> 0.92). The decision tree algorithm, SVM, and random forest approaches also have high prediction accuracy (> 77.9%) with low resubstitution error (< 14.3%), moderate specificity (> 0.5) and moderate sensitivity (> 0.2). The discriminant analysis, naive Bayes and KNN methods have relatively poor classification performance. Given these results for classification performance and prediction accuracy, the ANN is a good candidate for gait classifications for CP children with spastic diplegia. The decision tree is also attractive for clinical applications due to its transparency. Supervised machine learning algorithms can potentially be integrated into an expert gait analysis system that can interpret gait data and automatically generate high-quality analyses.

1. Introduction

Instrumented gait analysis has been widely used for children with cerebral palsy (CP) to assist with clinical decision making and to evaluate different treatment outcomes [1]. Based on temporal-spatial, kinematic, kinetic or electromyography data, clinicians can identify the gait pattern of a patient, classify this gait pattern into clinically significant categories, and plan appropriate interventions [2].

Several gait classification systems for CP children have been developed to differentiate gait patterns into clinically significant categories [3]. Of these, Rodda's system [3] has been widely used in clinical practice. The sagittal gait patterns are classified into several groups based on sagittal kinematics data, and include true equinus, jump gait, apparent equinus and crouch gait [3,4]. Although gait analysis can provide quantitative data, gait classification is still based on a clinician's subjective judgment and personal experience, which may increase the variability between different clinicians. An objective classification method for gait in CP with spastic diplegia is therefore required [5,6].

Previous studies have used unsupervised machine learning algorithms to construct gait classification. Cluster analysis methods are commonly used to draw inferences from data sets consisting of input data without labeled responses. For example, based on sagittal kinematics data for the ankle, knee, and hip joint, Kinenast et al. [7] identified normal and two pathological gait patterns of CP patients using the *k*-nearest neighbor (KNN) algorithm. Similar methods have also been used by several other studies to differentiate the gait patterns of spastic hemiplegia, spastic diplegia and spastic quadriplegia patients [8–10]. Rozumalski et al. identified five crouch gait patterns using a *k*-means cluster analysis based on gait features simplified from sagittal plane gait kinematics [11]. Rozumalski et al. also found that these five crouch gait patterns are significantly related to clinical pathologies such as age, range of motion of joints, strength, selective motor control and spasticity. Carriero et al. [12] employed principal component analysis and fuzzy C-means algorithms to classify gait patterns of CP patients

* Corresponding author. Department of Exercise Sciences, The University of Auckland, Private Bag 92019, Auckland, New Zealand.
E-mail address: yanxin.zhang@auckland.ac.nz (Y. Zhang).

https://doi.org/10.1016/j.compbiomed.2019.01.009
Received 20 August 2018; Received in revised form 13 January 2019; Accepted 14 January 2019
0010-4825/

with spastic diplegia based on temporal-spatial and kinematics data. Sangeux et al. [13] developed a quantitative classification system for sagittal gait patterns based on the plantar flexor-knee extension couple index and found that this classification system was highly accurate. Owais et al. used fuzzy clustering and adaptive neuro-fuzzy inference algorithms to group subjects with reconstructed anterior cruciate ligaments at different stages of recovery [14,15]. Using integrated features extracted from 3D kinematics of the tibiofemoral joint and electromyogram data, Owais et al. [14,15] achieved an accuracy of above 95% for gait classification at different walking speeds and above 80% for balance testing activities. The main limitation of unsupervised algorithms is that they may construct "artificial" groups that are not clinically meaningful. The lack of transparency of mathematical models also limits the reproducibility and clinical interpretation of these techniques.

Recently, supervised machine learning technologies have been applied to biomechanical research. A machine learning algorithm takes a known set of input data (e.g. gait parameters) and known responses to the data (e.g. type of gait), and trains a model to generate reasonable predictions for the responses to new data. Compared with unsupervised methods, supervised machine-learning algorithms may have the advantage of avoiding the construction of "artificial" groups by assigning suitable labels for training data based on predefined classes.

Mannini et al. [16] used the support vector machine (SVM) algorithm to classify different gait patterns for post-stroke patients, Huntington's disease patients, and healthy elderly people with an accuracy of 90.5%. Using SVM, Kamruzzaman et al. [17] classified gait patterns of CP patients and healthy controls with an overall accuracy of 83.33%, based only on two basic temporal-spatial gait parameters (stride length and cadence). Zhang et al. used SVM to group normal walking and fatigued states of walking with an accuracy of 96%, with the aim of detecting risk of fall and injury [18]. Carollo et al. [19] used hidden Markov models (HMM) to classify gait deviations in CP patients based on kinematics data. Armand et al. applied fuzzy decision trees to classify three gait patterns of toe-walking and obtained a classification accuracy of 81% [20]. According to the latest review of automatic recognition of pathological gait patterns (including stroke, spinal cord injury, Parkinson's disease, CP, multiple sclerosis, hip and knee osteoarthritis, and age-related gait impairment) using machine learning [21], Figueiredo et al. found that SVM stood out in the gait pattern recognition task, since it is accurate, can avoid over-fitting, and shows suitable generalization for new data [21].

Although several supervised machine learning algorithms have been proposed for gait classification, there is a lack of studies of the automatic classification of Rodda's gait classification system. There is also a lack of research comparing the performance of supervised machine learning classifiers for sagittal CP gait classifications based on the same data set, meaning that the classification performance and prediction accuracy of different supervised machine learning algorithms are unknown in CP gait classification. The aim of this study is therefore to evaluate seven supervised machine learning algorithms that are commonly used in the classification of sagittal gait patterns for CP children with spastic diplegia and to determine the most suitable algorithm for this task.

2. Methods

2.1. Data preparation

Gait data from two hundred CP children with spastic diplegia who had been assessed using instrumented gait analysis between 2010 and 2016 at the Bayi Rehabilitation Center (Chengdu, China) were reviewed to meet the inclusion criteria for this retrospective investigation. The inclusion criteria were: (1) diplegic spastic CP with symmetric gait; (2) age between six and 12 years old, (3) gross motor function classification system (GFMCS) ranking of I-II [1]; (4) capable of independent walking without assistance for more than three minutes; and (5) with no botulinum toxin injection in the lower extremities and/or surgery during the preceding six months.

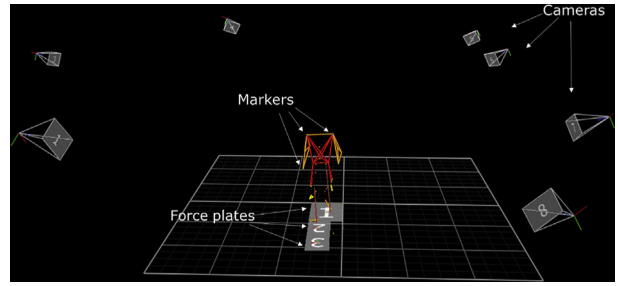

Fig. 1. The motion capture system used in this study.

In each individual gait trial, kinematic recordings of the lower limbs were reviewed. The data were recorded using an eight-camera motion analysis system (Vicon MX, Oxford Metrics, UK) and three force platforms (Fig. 1). The data collected by the cameras were synchronized with the ground reaction forces (GRF) recorded by the force plates. The cameras were positioned such that every marker was recorded at all times by at least two cameras. Marker placement followed the protocol for the Cleveland Clinic marker set. The subjects walked the length (12 m) of the laboratory barefoot at their natural speeds. Joint angles were computed using the Cleveland Clinic model [22].

The gait data were jointly evaluated by two biomechanists with more than ten years' experience in the interpretation of clinical gait data. Based on this evaluation, the gait pattern for each patient was classified as one of the following four groups: true equinus, jump gait, apparent equinus, and crouch gait, according to the definition by Rodda et al. [23], which is based on the sagittal kinematics of the ankle, knee, hip and pelvis joints. The four groups were defined as (1) true equinus, where the ankle is in equinus with full extension or mild recurvatum in the knee, normal hip and normal or anteriorly tilted pelvis; (2) jump gait, where the ankle is in equinus, especially in late stance phase, the knee and hip are excessively flexed in early stance and it is difficult to reach full extension, and the pelvis is within the normal range or anteriorly tilted; (3) apparent equinus, characterized by normal range ankle, excessively flexed knee and hip throughout stance phase; and (4) crouch gait, characterized by excessively dorsiflexed ankle and excessively flexed knee and hip [3,4]. This classification system was originally proposed based on clinical observations. A recent study also showed that it is feasible to group these gait patterns using statistical classification [13].

2.2. Construction of classification algorithms

The general procedure for the sagittal gait pattern classification for CP children with spastic diplegia is illustrated in Fig. 2. The first step was to prepare the training and test data. Lower limb joint angles were obtained via a standard inverse kinematic calculation. The key features of ankle, knee, and hip kinematics over a gait cycle were extracted. These features define a gait pattern [3,24] (see Fig. 3 and Table 1), and include maximal ankle plantar flexion (MaxAPF), maximal ankle dorsiflexion (MaxADF), maximal knee flexion (MaxKFlex), maximal knee extension (MaxKExt), maximum knee flexion at initial contact (MaxKFlexIC), maximal hip flexion (MaxHFlex), and maximal hip extension (MaxHExt). The features are the input data. We used a 10-fold cross-validation in this study.

Seven supervised machine learning algorithms [25] were used to construct the gait classification system: an artificial neural network (ANN), discriminant analysis, naive Bayes, decision tree (using the CART algorithm), SVM, random forest, and *k*-nearest neighbors (KNN). These algorithms have been successfully applied in a large number of machine learning classification problems with a great deal of practical

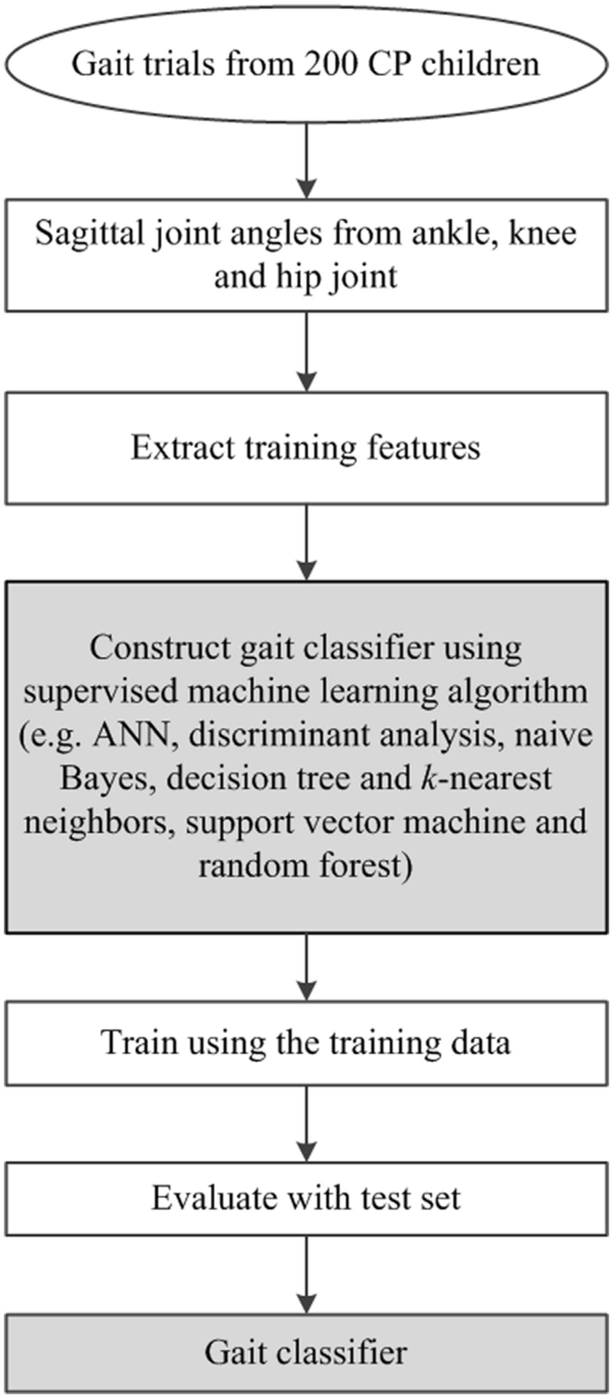

Fig. 2. Diagram of sagittal gait pattern classification using seven supervised machine learning algorithms.

success on large feature sets [26]. The ANN algorithm was implemented using IBM SPSS 22.0 software, while the others were implemented using Matlab 2017a.

For each of the seven machine learning algorithms, data are used as input to adjust the model parameters to match the known responses (gait types). Once the training is finished, the model is able to generate reasonable predictions.

2.2.1. Artificial neural network

In this study, an ANN with a multilayer perceptron algorithm (MLP) is employed. The algorithm consists of one input layer, one hidden layer and one output layer. The input layer has seven neurons, which are the seven key kinematics features ($x_1, x_2, \ldots, x_7$). The number of hidden layer neurons is 50. The output layer consists of four neurons, which are the corresponding four gait types (y_1, y_2, y_3, y_4). The MLP iteratively updates the weights to map the inputs to the outputs. Backpropagation is incorporated in the ANN algorithm to calculate the error contribution of each neuron after the input data are processed. The gradient descent optimization algorithm is used to adjust the weight of neurons to minimize the gradient of the cost function (1) [27]. The initial learning rate is 0.4, and the initial momentum parameter for the gradient descent algorithm is 0.9.

$$\mathrm{E} = \frac{1}{2}\sum_i (t_i - y_i)^T (t_i - y_i) \tag{1}$$

where t_i is the target output for pattern i.

2.2.2. Discriminant analysis

Discriminant analysis assumes that different classes generate data based on different Gaussian distributions [28]. To construct the classifier, a discriminant function estimates weighted combinations of variables with a Gaussian distribution for each class. Fisher's linear discriminant is used to maximize the ratio of between-class scatter to within-class scatter [29], and this algorithm was implemented using Matlab 2017a. The discriminant type is ‘linear,’ and the linear coefficient threshold is 0.

2.2.3. Naive Bayes

Naive Bayes is based on conditional probability theory. In this approach, classification is achieved by comparing scores with a predefined threshold based on the training set [30]. The algorithm leverages Bayes theory and assumes that the predictors are conditionally independent. The naive Bayes classifier assigns observations to the most probable class, i.e. the maximum posterior decision rule. The algorithm estimates the densities of the predictors for each class and models the posterior probabilities according to Bayes’ rule, shown in Equation (2). That is, for all $k = 1, \ldots, K$,

$$\hat{P}\left((Y = k|X_1, \ldots, X_P) = \frac{\pi\left(Y = k\right)\prod_{j=1}^{P} P(X_j|Y = k)}{\sum_{k=1}^{K} \pi\left(Y = k\right)\prod_{j=1}^{P} P(X_j|Y = k)}\right. \tag{2}$$

where Y is the random variable corresponding to the class index of an observation, $X_1, \ldots, X_P$ are the predictors of an observation, and $\pi(Y = k)$ is the prior probability that a class index is k.

2.2.4. Decision tree (using the CART algorithm) and random forest

A decision tree constructs classification or regression models in the form of a tree structure. This is built top-down from a root node, and involves partitioning the data into subsets that contain common features based on the level of information gain (the decrease in entropy after a dataset is separated) [31]. We used a standard classification and regression algorithm (CART) to select the best split predictor at each node [32].

As an extension of the decision tree algorithm, the random forest method uses an ensemble of decision trees and aggregates these into a single final result. The number of trees in this study is 50. This approach averages multiple deep decision trees that are trained on different parts of the same training set, with the goal of reducing the variance. Compared with a single tree, a random forest method can better avoid overfitting of the training data but may cause a small increase in the bias and some loss of interpretability.

2.2.5. Support vector machine

SVM classifies [33] two groups by constructing a set of hyperplanes in a high-dimensional space to separate the two groups. For a multi-class classification problem, the problem is converted to a set of

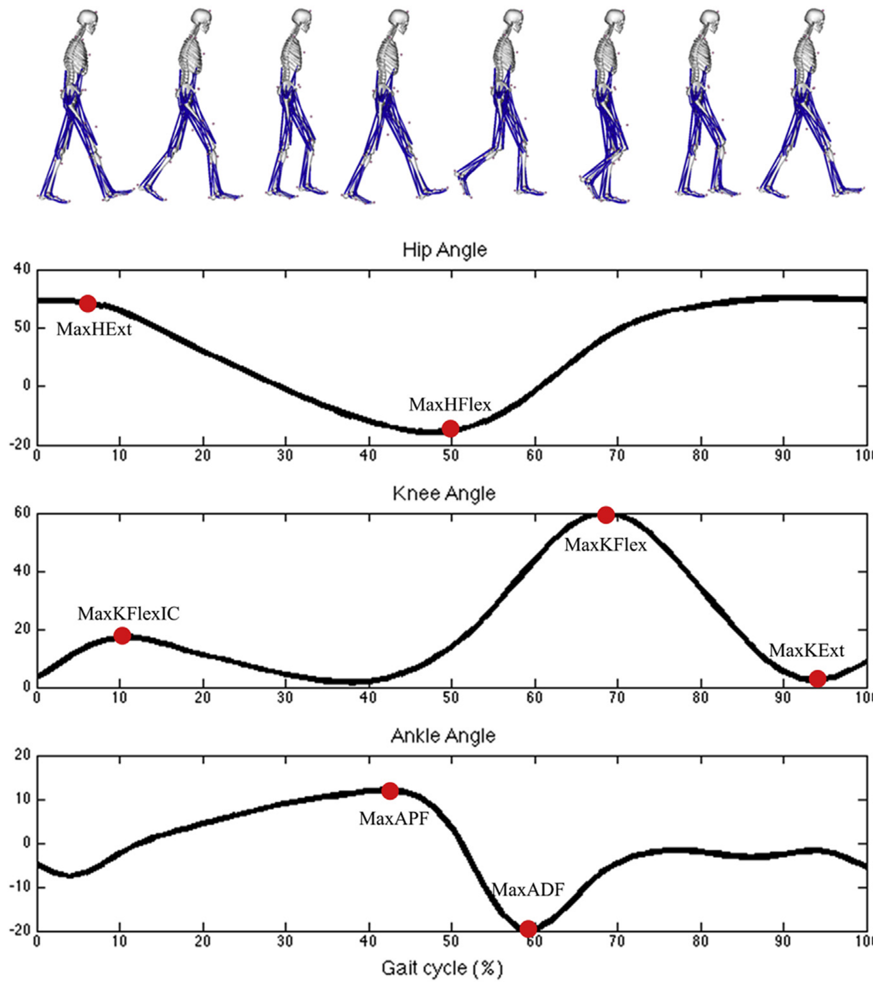

Fig. 3. Demonstration of seven features extracted from the entire gait cycle. Note: MaxAPF-maximal ankle plantar flexion, MaxADF-maximal ankle dorsiflexion, MaxKFlex-maximal knee flexion, MaxKExt-maximal knee extension, MaxKFlexIC-maximum knee flexion at initial contact, MaxHFlex-maximal hip flexion, and MaxHExt-maximal hip extension.

multiple binary classification problems. The kernel function we choose is 'linear' in this study (3).

$$K(x_i, x_j) = x_i' x_j \quad (3)$$

2.2.6. K-nearest neighbors

KNN computes the distance between the test object to the closest k objects in the training set and then determines a suitable class from the classes of these k objects [30]. Majority voting is used to combine the class labels. The distance is computed using the Euclidean distance as in Equation (4). The Euclidean distance between two points X= $(x_1, x_2, ..., x_n)$ and Y= $(y_1, y_2, ..., y_n)\varepsilon R$ is defined as:

$$D(X, Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (4)$$

2.3. Validation

We evaluated the seven supervised machine learning techniques and compared their performance for sagittal gait pattern recognition for CP children with spastic diplegia. To evaluate the predictive accuracy, the developed models underwent a standard 10-fold cross-validation procedure [34]. During this cross-validation, all of the data were partitioned into 10 sets at random. Nine of these sets were then used to develop a new model and to examine the predictive accuracy of this

Table 1
Mean and standard deviations of the key kinematic features of ankle, knee and hip joint for Rodda gait classification [3].

	True equinus		Jump gait		Apparent equinus		Crouch gait	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Ankle DF (°)	−3.2	8.5	−12.7	28.5	17.3	8.7	28.9	10.1
Ankle PF (°)	−29.7	18.3	−70.1	29.0	−24.5	15.3	−0.4	9.5
Knee Flex (°)	56.7	9.8	74.5	13.4	67.6	13.6	66.6	13.6
Knee Ext (°)	−3.8	10.9	20.0	19.3	15.6	10.3	18.8	12.3
Knee IC (°)	7.8	13.7	36.7	12.2	30.8	11.5	30.4	13.0
Hip Flex (°)	45.3	8.3	62.8	12.6	48.1	8.3	49.7	17.1
Hip Ext (°)	2.8	11.6	15.7	11.2	6.2	14.1	8.9	19.3

Table 2
The Resubstitution error and predictive accuracy of the seven machine learning algorithms.

	ANN	Discriminant analysis	Naive Bayes	Decision tree	KNN	SVM	Random Forests
Resubstitution error	5.8%	14.3%	13.6%	5.7%	0%	5.7%	6.4%
predictive accuracy	93.5%	84.3%	82.1%	84.3%	77.9%	85%	83.6%

model using the data from the tenth part. This was repeated 10 times, and each iteration used a different test set. The average of the 10 classification accuracy rates was taken as an unbiased estimate of the model for the complete dataset.

The resubstitution error, which is defined as the difference between the response training data and the predictions of the classifier, was calculated based on the input training data. The specificity, sensitivity and the area under the receiver operating characteristic curve (AUC) were also calculated for the seven machine learning algorithms. The sensitivity was a measure of the proportion of positive observations that were correctly identified as positive, while the specificity was a measure of the proportion of negatives that were truly negative [35]. AUC values were used to form a quantitative comparison in terms of their ability to distinguish between four sagittal CP gait patterns, where an AUC of 0.5 indicates a random classifier that has no value [36]. All three of these parameters have the range zero to one.

3. Results

Table 1 summarizes the seven gait kinematic features of the participants. Table 2 shows the results of the resubstitution error and the prediction accuracy of the 10-fold cross-validation for each of the seven algorithms. Table 3 shows the specificity, sensitivity and the area under the AUC of the selected seven machine learning algorithms.

Overall, the algorithms were generally able to classify the sagittal gait patterns from the training data correctly. With regard to the predictive accuracy of new data, the average was 84.4%. The ANN had the best prediction accuracy (93.5%). SVM, decision trees, and discriminant analysis achieved an accuracy of more than 84% for gait type classification. The ANN also had good classification performance with relatively low resubstitution errors (5.7%), high specificity (> 0.93), high sensitivity (> 0.92) and high AUCs (> 0.98). The decision tree exhibited fair classification performance for all gait types with low resubstitution errors (5.8%), high specificity (> 0.89), high sensitivity (> 0.75) and high AUCs (> 0.8). The sensitivity of the SVM for the classification of jump gait was 0.43, indicating that the SVM cannot group true jump gait correctly.

The KNN had the worst accuracy (78%) in gait classification for CP patients with spastic diplegia. Moreover, the sensitivity of the KNN when classifying apparent equinus was 0.54, indicating that the KNN could not group positive observations of apparent equinus well. The resubstitution errors for discriminant analysis and the naive Bayes algorithm were higher than for the other algorithms (14.3% and 13.6%, respectively). The AUCs for naive Bayes were 0.24 for apparent equinus and 0.5 for crouch gait, indicating that naive Bayes is not a suitable gait classifier for this task. The sensitivities of the discriminant analysis and the naive Bayes were 0.63 and 0.2, which also indicate poor positive classification of the CP gait patterns.

Table 3
The specificity, sensitivity and the area under the ROC curve (AUC) of the seven machine learning algorithms.

		Apparent equinus	Crouch gait	Jump gait	True equinus
Decision tree	Specificity	0.89	0.9	0.99	0.98
	Sensitivity	0.77	0.89	0.86	0.75
	AUC	0.8	0.89	0.92	0.91
Discriminant analysis	Specificity	0.92	0.84	0.98	0.97
	Sensitivity	0.63	0.95	0.71	0.75
	AUC	0.9	0.97	0.98	0.99
KNN	Specificity	0.9	0.72	0.95	0.98
	Sensitivity	0.54	0.98	0.85	0.75
	AUC	0.84	0.95	0.92	0.99
Naive Bayes	Specificity	0.8	0.5	0.85	0.97
	Sensitivity	0.2	0.95	0.85	0.88
	AUC	0.24	0.5	0.74	0.87
ANN	Specificity	0.93	0.98	1	0.99
	Sensitivity	0.92	0.97	1	1
	AUC	0.98	0.99	1	1
SVM	Specificity	0.92	0.84	0.99	0.98
	Sensitivity	0.71	0.95	0.43	0.81
	AUC	0.88	0.96	0.98	0.98
Random Forests	Specificity	0.96	0.93	0.96	0.96
	Sensitivity	0.69	0.9	0.71	0.69
	AUC	0.95	0.98	0.96	0.95

4. Discussion

Of the seven algorithms, the ANN achieved the highest accuracy (93.5%) for gait pattern classification. The classification accuracy of the other algorithms (77.9%–85%) was generally within the same range as previous gait classification studies using ANN algorithms and fuzzy decision trees. The accuracy of classification of gait data with neural networks has been reported as being around 80% [37]. Armand et al. applied fuzzy decision trees to classify three kinematic ankle gait patterns of toe-walking and obtained a classification accuracy of 81%. In comparison with other studies [38] of falling detection using the same algorithms, our prediction accuracy is much lower. One possible reason for this is that the complexities of the two systems are different: a falling detection algorithm only needs to separate one class (falling) from another (non-falling), while gait classification needs to identify a single gait pattern from several others, which increases the chances of false detection.

There are several factors that may affect the prediction accuracy. Firstly, the gait patterns used in this study are defined by clinical observations, and have very good clinical interpretations [23]. However, there were no clear boundaries between the different gait patterns. As shown in Table 1, there are overlaps between a number of kinematic parameters. As a result, the classification algorithms are not able to achieve low resubstitution errors based on the training data. Large resubstitution errors can affect the accuracy of prediction for new data. Secondly, the prediction accuracy is also affected by the sample size of the training data. In this study, we used 200 gait trials; a larger sample size may generate better results.

The ANN algorithm, which achieved the highest prediction accuracy and the best classification performance, can implicitly detect complex nonlinear relationships between the input and the output, and can detect possible interactions between predictor variables better than the other methods [27]. ANNs can also usually provide incremental learning more easily. However, the most striking disadvantage of ANNs is the lack of transparency of their mathematical models, which fail to justify their output in a way that can be effectively interpreted. For this reason, future work should address the issue of improving the

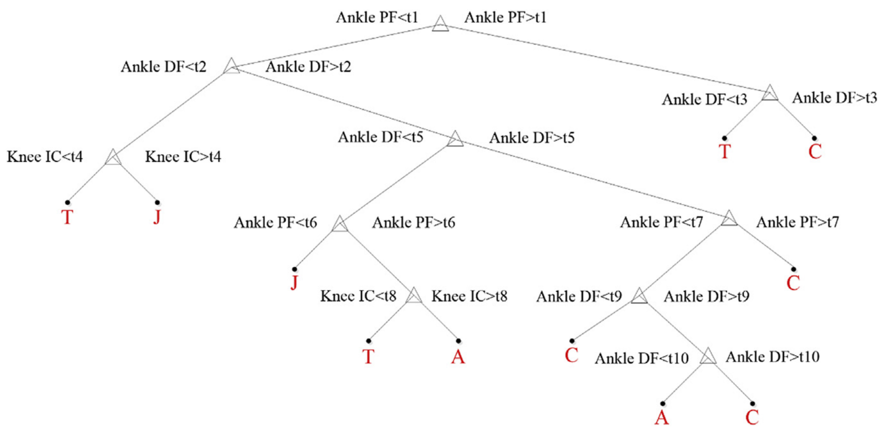

Fig. 4. Illustration of the decision tree process. The character "A" represents apparent equines; "C" crouch gait, "J" jump gait, and "T" true equinus. "t1" to "t10" are the threshold values of each tree node. Ankle PF, Ankle DF and Knee IC represent ankle plantar flexion, ankle dorsiflexion and knee flexion at the initial contact, respectively.

comprehensibility of neural networks, and the most attractive solution would be to extract symbolic rules from trained neural networks.

Besides the ANN, the decision tree is another good candidate for future use and for further investigation. Although the prediction accuracy of the decision tree is lower than that of the ANN, the classification process of the algorithm is transparent, and the model structure of the entire procedure can therefore be followed. Using our study as an example (Fig. 4), we can see that the decision tree first compares ankle plantar flexion (PF) with a threshold, and the data are then separated into two subsets. The partition of each subset is based on a specific value of ankle dorsiflexion (DF). The partition continues at each tree node until a gait type is classified. The decision tree is also easy to understand and implement, is computationally efficient, and is easy to test and evaluate. In previous research, Armand et al. [39] used a fuzzy decision tree to create intelligible rules to link toe-walking patterns to their possible clinical causes. These rules can potentially improve the understanding and interpretation of certain sub-type gait patterns that were not revealed by empirical gait analysis and clinical observations. In our study, the decision tree also provides this type of information (Fig. 4). There are four sub-types of crouch gait patterns, three sub-types of true equinus gait patterns, two sub-types of apparent equinus gait patterns and two sub-types of jump gait patterns. The possible clinical cause of each sub-type gait pattern may be different, and this needs further investigation. Another interesting finding is that the algorithm only employed three parameters (ankle DF, ankle PF, and knee IC) to group the gait patterns. This finding may indicate that ankle DF, ankle PF, and knee IC are the most important parameters in gait classification for CP with spastic diplegia.

This research has several clinical implications. As discussed in the introduction, gait classification may enable clinicians to differentiate gait patterns into clinically significant categories that can assist in clinical decision making. The gait classification method developed in this project can potentially be integrated into an expert gait analysis system that can classify gait data and automatically generate high-quality analysis. This expert system would free clinicians from the task of manual classification. For instance, the system could be used as a plug-in package for an existing motion capture system and thereby add value to its gait assessment solution. More recently, advances in motion capture technology and computational methods have made it possible to use low-cost, high-quality, light, small sensors, e.g. inertia sensors, to track human motion. A portable system could make motor impairment assessment more convenient and improve the quality of rehabilitation, especially in rural areas. Our future work will therefore focus on developing an intelligent system for automated motor impairment assessment that will combine motion capture technology and enhanced intelligent algorithms.

5. Conclusion

The aim of this study was to evaluate the performance of seven supervised machine learning algorithms in order to determine the most suitable algorithm for use in gait classification for CP children with spastic diplegia using kinematic features of the lower limbs. In terms of both the prediction accuracy and classification performance, ANN showed the best performance. The decision tree is another good candidate for gait classification in CP with spastic diplegia. In addition to its good prediction accuracy and classification performance, the algorithm is also transparent, computationally efficient, and is easy to use and evaluate. Supervised machine learning algorithms can potentially be integrated into a gait analysis expert system that can interpret gait data and generate high-quality analysis automatically.

Conflicts of interest

No.

Acknowledgments

The authors would like to thank the technicians who collected the data from Bayi Rehabilitation hospital. There was no support in the form of funding for this study.

References

[1] H.K. Graham, P. Selber, Musculoskeletal aspects of cerebral palsy, Journal of Bone and Joint Surgery-British 85B (2) (2003) 157–166.
[2] F.M. Chang, J.T. Rhodes, K.M. Flynn, J.J. Carollo, The role of gait analysis in treating gait abnormalities in cerebral palsy, Orthop. Clin. N. Am. 41 (4) (2010) 489–506.
[3] J. Rodda, H. Graham, L. Carson, M. Galea, R. Wolfe, Sagittal gait patterns in spastic diplegia, Bone & Joint Journal 86 (2) (2004) 251–258.
[4] J. Rodda, H.K. Graham, Classification of gait patterns in spastic hemiplegia and spastic diplegia: a basis for a management algorithm, Eur. J. Neurol. 8 (Suppl 5) (2001) 98–108.
[5] F. Dobson, M.E. Morris, R. Baker, H.K. Graham, Gait classification in children with cerebral palsy: a systematic review, Gait Posture 25 (1) (2007) 140–152.
[6] A. Rozumalski, M.H. Schwartz, Crouch gait patterns defined using k-means cluster analysis are related to underlying clinical pathology, Gait Posture 30 (2) (2009) 155–160.
[7] G. Kienast, D. Bachmann, G. Steinwender, E.-B. Zwick, V. Saraph, Determination of gait patterns in children with cerebral palsy using cluster analysis, Gait Posture 10 (1) (1999) 57.
[8] J.M. O'Byrne, A. Jenkinson, T. O'brien, Quantitative analysis and classification of gait patterns in cerebral palsy using a three-dimensional motion analyzer, J. Child Neurol. 13 (3) (1998) 101–108.
[9] M.J. O'Malley, M.F. Abel, D.L. Damiano, C.L. Vaughan, Fuzzy clustering of children with cerebral palsy based on temporal-distance gait parameters, IEEE Trans. Rehabil. Eng. 5 (4) (1997) 300–309.
[10] M.A. Wong, S. Simon, R.A. Olshen, Statistical analysis of gait patterns of persons with cerebral palsy, Stat. Med. 2 (3) (1983) 345–354.
[11] A. Rozumalski, M.H. Schwartz, Crouch gait patterns defined using k-means cluster analysis are related to underlying clinical pathology, Gait Posture 30 (2) (2009)

155–160.
[12] A. Carriero, A. Zavatsky, J. Stebbins, T. Theologis, S.J. Shefelbine, Determination of gait patterns in children with spastic diplegic cerebral palsy using principal components, Gait Posture 29 (1) (2009) 71–75.
[13] M. Sangeux, J. Rodda, H.K. Graham, Sagittal gait patterns in cerebral palsy: the plantarflexor–knee extension couple index, Gait Posture 41 (2) (2015) 586–591.
[14] S.A. Senanayake, O.A. Malik, P.M. Iskandar, D. Zaheer, A knowledge-based intelligent framework for anterior cruciate ligament rehabilitation monitoring, Appl. Soft Comput. 20 (2014) 127–141.
[15] O.A. Malik, S.A. Senanayake, D. Zaheer, An intelligent recovery progress evaluation system for ACL reconstructed subjects using integrated 3-D kinematics and EMG features, IEEE J. Biomedical and Health Informatics 19 (2) (2015) 453–463.
[16] A. Mannini, D. Trojaniello, A. Cereatti, A.M. Sabatini, A machine learning framework for gait classification using inertial sensors: application to elderly, post-stroke and huntington's disease patients, Sensors 16 (1) (2016).
[17] J. Kamruzzaman, R.K. Begg, Support vector machines and other pattern recognition approaches to the diagnosis of cerebral palsy gait, IEEE (Inst. Electr. Electron. Eng.) Trans. Biomed. Eng. 53 (12) (2006) 2479–2490.
[18] J. Zhang, T.E. Lockhart, R. Soangra, Classifying lower extremity muscle fatigue during walking using machine learning and inertial sensors, Ann. Biomed. Eng. 42 (3) (2014) 600–612.
[19] J. Carollo, Q. He, C. Debrunner, Gait pattern classification in children with cerebral palsy: results from a 12-state hidden Markov model created with a large training set, Gait Posture S 20 (2004) S4.
[20] S. Armand, E. Watelain, E. Roux, M. Mercier, F.-X. Lepoutre, Linking clinical measurements and kinematic gait patterns of toe-walking using fuzzy decision trees, Gait Posture 25 (3) (2007) 475–484.
[21] J. Figueiredo, C.P. Santos, J.C. Moreno, Automatic recognition of gait patterns in human motor disorders using machine learning: a review, Med. Eng. Phys. 53 (2018) 1–12.
[22] A.H. Mackey, S.E. Walt, G.A. Lobb, N.S. Stott, Reliability of upper and lower limb three-dimensional kinematics in children with hemiplegia, Gait Posture 22 (1) (2005) 1–9.
[23] J.M. Rodda, H.K. Graham, L. Carson, M.P. Galea, R. Wolfe, Sagittal gait patterns in spastic diplegia, J Bone Joint Surg Br 86 (2) (2004) 251–258.
[24] J. Perry, J.R. Davids, Gait analysis: normal and pathological function, J. Pediatr. Orthop. 12 (6) (1992) 815.
[25] X. Wu, V. Kumar, J. Ross Quinlan, J. Ghosh, Q. Yang, H. Motoda, G.J. McLachlan, A. Ng, B. Liu, P.S. Yu, Z.-H. Zhou, M. Steinbach, D.J. Hand, D. Steinberg, Top 10 algorithms in data mining, Knowl. Inf. Syst. 14 (1) (2008) 1–37.
[26] S.B. Kotsiantis, Supervised machine learning: a review of classification techniques, Proceedings of the 2007 Conference on Emerging Artificial Intelligence Applications in Computer Engineering: Real Word AI Systems with Applications in eHealth, HCI, Information Retrieval and Pervasive Technologies, IOS Press, 2007, pp. 3–24.
[27] T. Chau, A review of analytical techniques for gait data. Part 2: neural network and wavelet methods, Gait Posture 13 (2) (2001) 102–120.
[28] J.Y. Goulermas, A.H. Findlow, C.J. Nester, D. Howard, P. Bowker, Automated design of robust discriminant analysis classifier for foot pressure lesions using kinematic data, IEEE (Inst. Electr. Electron. Eng.) Trans. Biomed. Eng. 52 (9) (2005) 1549–1562.
[29] C. Bishop, C.M. Bishop, Neural Networks for Pattern Recognition, Oxford university press, 1995.
[30] X. Wu, V. Kumar, J.R. Quinlan, J. Ghosh, Q. Yang, H. Motoda, G.J. McLachlan, A. Ng, B. Liu, S.Y. Philip, Top 10 algorithms in data mining, Knowl. Inf. Syst. 14 (1) (2008) 1–37.
[31] S.R. Safavian, D. Landgrebe, A survey of decision tree classifier methodology, IEEE transactions on systems, man, and cybernetics 21 (3) (1991) 660–674.
[32] P. Breheny, Classification and Regression Trees, (1984).
[33] V. Vapnik, The Nature of Statistical Learning Theory, Springer science & business media, 2013.
[34] G.J. McLachlan, K.A. Do, C. Ambroise, Analyzing Microarray Gene Expression Data. Wiley Series in Probability and Statistics, Wiley-Interscience. xx, Hoboken, N.J., 2004 320 pp..
[35] Z. Zhang, Introduction to machine learning: k-nearest neighbors, Ann. Transl. Med. 4 (11) (2016).
[36] D.J. Hand, R.J. Till, A simple generalisation of the area under the ROC curve for multiple class classification problems, Mach. Learn. 45 (2) (2001) 171–186.
[37] W.I. Schöllhorn, Applications of artificial neural nets in clinical biomechanics, Clin. BioMech. 19 (9) (2004) 876–898.
[38] M.V. Albert, K. Kording, M. Herrmann, A. Jayaraman, Fall classification by machine learning using mobile phones, PLoS One 7 (5) (2012) e36556.
[39] S. Armand, E. Watelain, E. Roux, M. Mercier, F.X. Lepoutre, Linking clinical measurements and kinematic gait patterns of toe-walking using fuzzy decision trees, Gait Posture 25 (3) (2007) 475–484.

Yanxin Zhang received his B.S. degree in instrumentation engineering from Shanghai Jiao Tong University in 2000 and Ph.D. degree in industrial engineering from Texas Tech University in 2005. He worked as a Post-Doctoral Research Associate in the Department of Kinesiology of the Arizona State University from 2005 to 2006. From 2006 to 2008, he worked as a research associate in the School of Human Movement and Exercise Science of the University of Western Australia. He is currently a senior lecturer and the director of the biomechanics laboratory from the department of Exercise Sciences of the University of Auckland. His research is concentrated on the development of biomechanical methods to simulate, evaluate and optimize human motions, which could create theoretical basis of developing effective approach for rehabilitation and functional restoration after neuromuscular injury. He has published over 60 papers in peer-reviewed journals and prestigious international conferences. Dr. Zhang is a member of Society of Neural Control of Movement, Human factors and Ergonomics Society, and Automotive Engineers Society.

Ye Ma received her B.E. degree in vehicle engineering from Shandong University of Technology in 2009 and M.E. degree in vehicle operation engineering from Tongji University in 2012. She received her Ph.D. degree in mechanical engineering from the University of Auckland in 2017. She is currently a lecturer of the Research Academy of Grand Health of Ningbo University. Her research interests are control strategies of gait rehabilitation robots, human-robot interaction, gait analysis, musculoskeletal modelling and simulation, and electromyography-driven models for robotic applications. She has published 9 papers in peer-reviewed journals and prestigious international conferences.