Diagnosis of lameness in dogs by use of artificial neural networks and ground reaction forces obtained during gait analysis

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Objective—To evaluate the accuracy of artificial neural networks (ANNs) for use in predicting subjective diagnostic scores of lameness with variables determined from ground reaction force (GRF) data.

Animals—21 adult mixed-breed dogs.

Procedures—The left cranial cruciate ligament of each dog was transected to induce osteoarthritis of the stifle joint as part of another study. Lameness scores were assigned and GRF data were collected 2 times before and 5 times after ligament transection. Inputs and the output for each ANN were GRF variables and a lameness score, respectively. The ANNs were developed by use of data from 14 dogs and evaluated by use of data for the remaining 7 dogs (ie, dogs not used in model development).

Results—ANN models developed with 2 preferred input variables had an overall accuracy ranging from 96% to 99% for 2 data configurations (data configuration 1 contained patterns or observations for 7 dogs, whereas data configuration 2 contained patterns or observations for 7 other dogs). When additional variables were added to the models, the highest overall accuracy ranged from 97% to 100%.

Conclusions and Clinical Relevance—ANNs provided a method for processing GRF data of dogs to accurately predict subjective diagnostic scores of lameness. Processing of GRF data via ANNs could result in a more precise evaluation of surgical and pharmacological intervention by detecting subtle lameness that could have been missed by visual analysis of GRF curves. (*Am J Vet Res* 2012;73:973–978)

Force plate analysis of the gait in dogs is a reliable means of assessing limb function and the efficacy of various medical and pharmacological interventions.[1–5] The advantage of force plate analysis is that it readily measures GRFs, which are equal in magnitude but opposite in direction to the net internal force generated during locomotion. These data are precise and repeatable.[3–7] However, the relationships between subjective lameness scores and GRF data are not yet fully understood, even though correlations have been detected.[2,6,7] A major challenge to gaining a full understanding of these relationships is that GRF data sets are generated with multiple foot or paws strikes on a GRF plate, which makes it difficult to assess the forces for a specific limb. A study[8] of pathological GRF patterns in which there were multiple foot strikes was conducted to address this challenge through the use of a neural network–based analysis, and investigators found that ANNs could be applied to estimate missing GRF data. Thus, there is a potential for a similar neural network–based process that duplicates an expert's diagnosis of lameness in an animal. Such a process could be a useful diagnostic tool for situations in which lameness makes it difficult to collect GRF data sets with single paw strikes.

Abbreviations

ANN	Artificial neural network
GRF	Ground reaction force
LF	Left forelimb
LH	Left hind limb
PFz	Peak vertical force
RF	Right forelimb
RH	Right hind limb
MidL	Minimum point between the peak vertical force on the left limbs
MidR	Minimum point between the peak vertical force on the right limbs
MidR–L	Difference between the minimum point between the peak vertical force on the left limbs and the minimum point between the peak vertical force on the right limbs

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An ANN is a computational model that simulates the biological learning process of a brain and has been used to process human and equine GRF data.[9–16] Artificial neural networks consist of 3 elements: processing units (referred to as nodes), links or weights that connect the nodes, and mathematical learning rules. In a process known as supervised learning, an ANN derives meaning from complicated data by use of examples of a known set of inputs and corresponding target outputs. One of the major advantages of the use of ANNs in a clinical decision support system is that ANNs can use previously acquired gait data to make a diagnosis about a similar but not identical observation. This characteristic is valuable because investigators need not be certain how the factors in the data interact or contribute to the final diagnosis.

Artificial neural networks are suited for classification of data that cannot be understood and interpreted correctly by machines (eg, GRF data that reflect a dog's movement and its inner musculoskeletal activity as a whole). The use of ANNs has been effective for detecting gait abnormalities in humans and horses.[9–17] The purpose of the study reported here was to assess the accuracy of ANNs via input variables extracted from canine GRF data to predict a subjective diagnostic score of lameness. Related objectives were to identify the important input variables from the GRF data and evaluate the results for use in an automated lameness diagnostic system for dogs.

Materials and Methods

Animals—Twenty-one clinically normal adult mixed-breed dogs that weighed from 19 to 32.2 kg (mean, 24.4 kg) were used in the study. The cranial cruciate ligament in the hind limb of each dog was transected to induce osteoarthritis of the stifle joint as part of another study.[18] All procedures were approved by the University of Georgia Animal Care and Use Committee.

Gait data collection—The GRF data were collected by use of 2 biomechanical force plates[a] that were level with the surface of and located in the center of a 12-m walkway. The GRF data were recorded at 1-millisecond intervals by use of data acquisition software.[b] Concurrent to each GRF data collection period, each dog was assigned a lameness score by use of a 4-point scoring system[18] (1, no lameness during trotting; 2, slight lameness during trotting; 3, moderate lameness during trotting; and 4, severe lameness during trotting). The investigator performing the lameness scoring (SCB) was not aware of any of the GRF data.

Subjective diagnostic scores were assigned and GRF data collected for 7 trials. The trials were conducted 1 month before, immediately before, and 1, 3, 6, 9, and 12 months after ligament transection. For each trial, 5 valid GRF observations were collected for each dog. The GRF data were considered valid when the velocity during trotting was between 1.7 and 2.1 m/s with acceleration variation between –0.5 to 0.5 m/s^2. Five light-beam sensors spaced at intervals of 0.8 m were placed across the control area of the force plate; measurement of the amount of time it took a dog to break each beam provided objective measurements of velocity and acceleration.

A total of 678 gait patterns were obtained for the 21 dogs. All the dogs were judged to be clinically normal (lameness score, 1) before the ligament transection, and all of them were slightly (lameness score, 2) or moderately (lameness score, 3) lame during trotting 1 month after the surgery. The lameness score of some dogs fluctuated after the surgery. Only 9 dogs received scores of 1, 2, and 3, whereas the remaining 12 dogs received scores of 1 and 2. None of the dogs ever were considered severely lame (lameness score, 4). A total of 265, 354, and 59 observations for dogs with lameness scores of 1, 2, and 3, respectively, were obtained.

ANN design tools and procedure—Artificial neural networks were developed by use of a commercial package[c] to map a set of GRF variables to a corresponding lameness score (1, 2, or 3). Standard 3-layer back propagation ANNs **(Figure 1)** were selected because they have been used to detect abnormalities in gaits of humans and horses.[9–15,17] A limited search for optimal ANN architecture parameters was performed, and the resulting values for the parameters were as follows: number of hidden nodes, 2; learning rate, 0.1; momentum, 0.1; initial weight range, ± 0.3 kg; activation function (input layer), linear; activation function (hidden layer), logistic; and activation function (output layer), logistic.

The model development process involved 4 steps: creation of ANN data patterns from the GRF data and lameness diagnosis, partitioning of the data set, training of ANNs, and assessment of ANN accuracy for the evaluation data set. First, GRF input variables and corresponding output target values from a single observation were organized into a pattern, and all the patterns acquired were organized into a data set. The target values of training patterns for lameness scores 1, 2, and 3 were 0.1, 0.5, and 0.9, respectively. The ANN output, determined by use of the logistic function, was a value between 0 and 1. Therefore, 2 thresholds of 0.35 and 0.65 were arbitrarily selected to convert the continuous output of the trained ANN into the 3 classes of lameness scores (1, 2, and 3).

Second, to develop and evaluate each ANN, the data set was divided into 2 mutually exclusive data sets (model development and model evaluation). The model development data set was further divided into train-

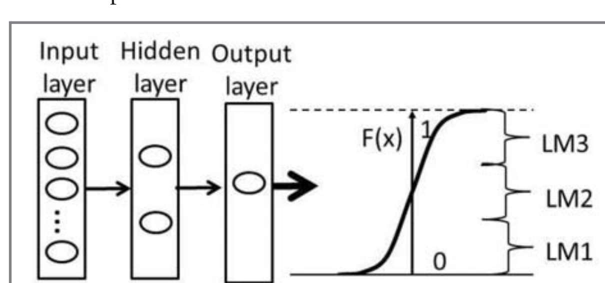

Figure 1—Schematic diagram of an ANN with an input layer, a hidden layer, and an output layer for differentiation of 3 classes of lameness (LM1 = no lameness during trotting, LM2 = slight lameness during trotting, and LM3 = moderate lameness during trotting) in dogs. Results for F(x), which is the logistic activation function where x is the net input from the hidden layer, are used to diagnose lameness. Thresholds for the lameness classes are as follows: LM1, 0 to 0.35; LM2, > 0.35 to 0.65; and LM3, > 0.65 to 1.00.

ing and testing data sets. The training data set was used with the back propagation algorithm to search for the optimal set of ANN weights or link-connection strength to minimize error. The testing data set was used to determine when the back propagation training process should be stopped to avoid overfitting. If an ANN was trained until the difference between output value and the corresponding target value (error) on a training data set was minimized, then the network might learn of noise or features specific to the training data set in addition to the important features. The testing data set was provided to the ANN periodically (ie, every 200 training patterns provided) during training in feed-forward mode only. This process was repeated until the error for the testing data set was reasonably minimized (ie, no improvement was found for the testing data set after 20,000 training patterns since the minimum error on the testing data set had been found). The ability of the model to generalize was aided when the training was stopped because of a minimum error for the test set. Once the model was developed, patterns in the evaluation data set were provided to the trained network in feed-forward mode only to determine the performance of the model for the new data observations.

The model development data consisted of patterns from two-thirds of the dogs (n = 14) in the data set, and the model evaluation data set consisted of patterns from the remaining 7 dogs. To obtain results that would closely correspond to model performance in clinical practice, the accuracy of each model assessed by use of this model evaluation data set never contained patterns from a dog included in the model development data set.

The ANNs were developed and evaluated by use of partitioning of the data into 2 subsets (data configurations 1 and 2). To provide additional validation, the evaluation data set of data configuration 2 was constrained to avoid patterns from dogs included in the evaluation data set of data configuration 1. Therefore, the evaluation data set of data configuration 1 contained patterns or observations for 7 dogs, whereas the evaluation data set of data configuration 2 contained patterns for 7 other dogs. However, because only 9 dogs had a lameness score of 3, both evaluation data sets contained patterns from 3 dogs with 3 patterns and patterns from 4 other randomly selected dogs.

Third, once an ANN was trained and the results from the evaluation data set were obtained, a predicted lameness score was assigned to each pattern in the evaluation data set. The continuous output value of the back propagation ANN was interpreted as lameness score 1, 2, or 3 when it was within the range of 0 to 0.35, > 0.35 to 0.65, or > 0.65 to 1.00, respectively.

Finally, each ANN was assigned an overall accuracy. The overall accuracy was the sum of the patterns classified the same as the lameness scores assigned by the expert divided by the total number of patterns in the evaluation data set.

Input variables—Inputs to each network were variables extracted from GRF curves. Variables used for statistical analysis of the canine gait data were PFzs for the LF, RF, LH, and RH; peak braking forces; peak propulsive forces; peak medial-lateral forces; associated impulses (vertical, braking, propulsive, and medial-lateral); limb-loading and -unloading time; and limb-loading and -unloading rate (**Figure 2**). Loading rate was defined as the mean slope of the loading portion of the GRF curves, and unloading rate was defined as the mean slope of the unloading portion of the GRF curves.

Other input variables extracted from the GRF curves were the weight distribution among all 4 limbs and the minimum point between the PFzs of ipsilateral limbs (ie, MidL, MidR, and MidR–L), which were designated as midlevel variables (**Figure 3**).

It should be mentioned that the degree of lameness could result in GRF curves in which the midlevel variables did not return to a force magnitude of 0. The 3 factors that affected MidR and MidL were forelimb and hind limb stance-phase overlap; forelimb loading and

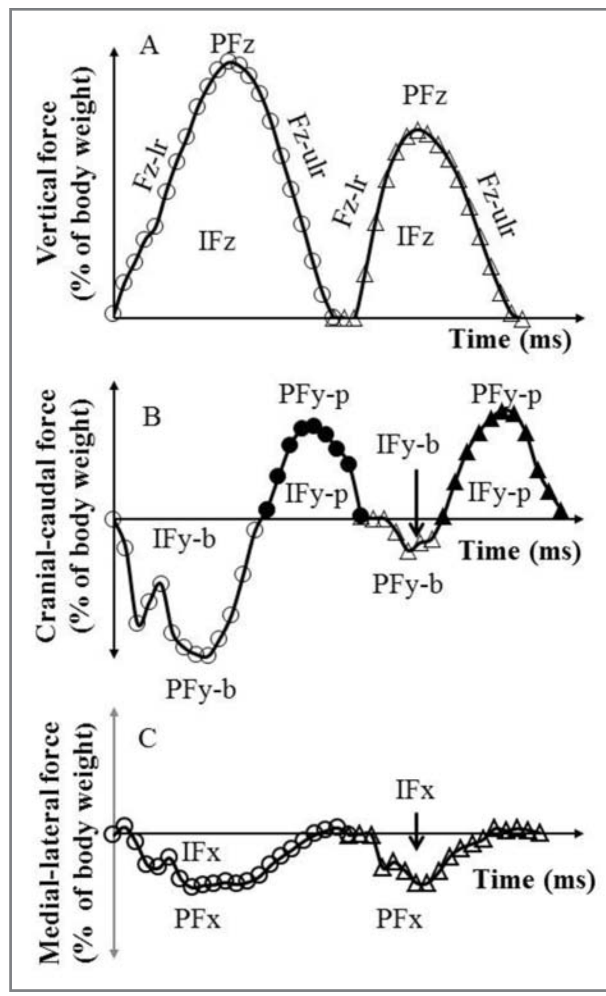

Figure 2—Representative GRF curves of the gait in clinically normal dogs. Panel A is representative vertical force curves for the forelimbs (white circles) and the hind limbs (white triangles), panel B is representative cranial-caudal force curves for the forelimbs during braking (white circles) and during propulsion (black circles) and for the hind limbs during braking (white triangles) and during propulsion (black triangles), and panel C is representative medial-lateral force curves for the forelimbs (white circles) and the hind limbs (white triangles). Fz-lr = Vertical loading rate. Fz-ulr = Vertical unloading rate. IFx = Medial-lateral impulse (area under the curve). IFy-b = Braking impulse (area under the curve). IFy-p = Propulsion impulse (area under the curve). IFz = Vertical impulse (area under the curve). PFx = Peak medial-lateral force. PFy-b = Peak braking force. PFy-p = Peak propulsion force.

unloading rate, which is affected by the PFz of the forelimb (LF or RF) and unloading time of the forelimb; and the hind limb loading rate, which is affected by the PFz on the hind limb (LH or RH) and loading time of the hind limb.

The objective for use of the ANNs was to find relationships among the available inputs to generate an output that approximated the target output. Several inputs were created from the GRF data and used to train the ANN model, which then attempted to duplicate the expert's diagnosis of lameness. The midlevel variables MidR and MidL were normalized on the basis of the sum of the PFzs of any set of limbs and then used as input variables. The ANN used these new normalized input variables (Figure 3). For example, MidR and MidL were normalized first on the basis of PFz of the RF plus PFz of the LF and subsequently by PFz of the RH plus PFz of the LH, PFz of the RF plus PFz of the LH, PFz of the LF plus PFz of the RH, PFz of the RF plus PFz of the RH, and finally PFz of the LF plus PFz of the LH. These normalized parameters were found to be the best input variables that would yield the most accurate ANN.

Procedure for selection of preferred input variables—Several ANNs were developed to examine the impact of individual input variables as well as a set of input variables on the accuracy. An ANN was trained by use of each input variable individually. Combinations of the single input variables found to be useful were then used to create additional ANNs. When multiple inputs increased the accuracy of an ANN, these variables, in addition to other input variables, were used to develop additional ANNs. When the accuracy of an ANN was lower with the multiple inputs, alternative combinations were tested. After this process was repeated, unnecessary input variables were eliminated and useful variables were kept for subsequent model development.

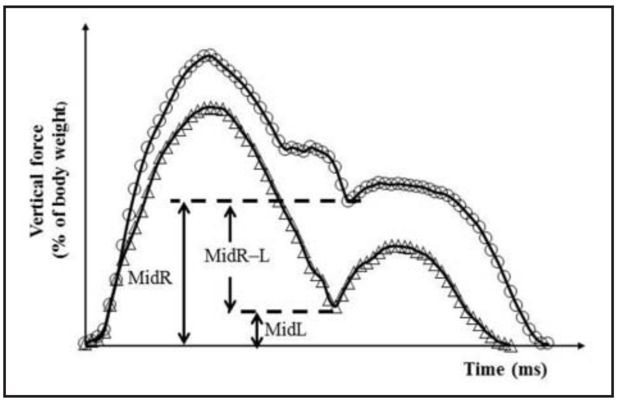

Figure 3—Representative GRF curves of the vertical force of the left (triangles) and right (circles) limbs of dogs with regard to MidL, MidR, and MidR–L input variables used in ANNs for the diagnosis of lameness.

Table 1—Overall accuracy for diagnosis of lameness in dogs with ANNs developed by use of single-input variables related to midlevel measurements obtained from GRF data.

Input variable	Overall accuracy (%)
MidR	57
MidR/(PFz of the RF + PFz of the LF)	57
MidR/(PFz of the RH + PFz of the LH)	57
MidR/(PFz of the RF + PFz of the LH)	57
MidR/(PFz of the LF + PFz of the RH)	57
MidR/(PFz of the RF + PFz of the RH)	57
MidR/(PFz of the LF + PFz of the LH)	58
MidR/(PFz of the RF + PFz of the LF + PFz of the LH)	56
MidR/(PFz of the RH + PFz of the LF + PFz of the LH)	56
MidR/(PFz of the RF + PFz of the RH + PFz of the LH)	56
MidR/(PFz of the RF + PFz of the RH + PFz of the LF)	55
MidR–L	55
MidR–L/(PFz of the RF + PFz of the LF)	94
MidR–L/(PFz of the RH + PFz of the LH)	91
MidR–L/(PFz of the RF + PFz of the LH)	56
MidR–L/(PFz of the LF + PFz of the RH)	55
MidR–L/(PFz of the RF + PFz of the RH)	63
MidR–L/(PFz of the LF + PFz of the LH)	91
MidR–L/(PFz of the RF + PFz of the LF + PFz of the LH)	56
MidR–L/(PFz of the RH + PFz of the LF + PFz of the LH)	57
MidR–L/(PFz of the RF + PFz of the RH + PFz of the LH)	56
MidR–L/(PFz of the RF + PFz of the RH + PFz of the LF)	57

Results

Results of ANNs with a single input variable were summarized **(Table 1)**. Variables with the greatest indication of success were the MidR–Ls divided by the sum of the PFzs for each limb. The accuracies of ANNs with MidR–L/(PFz of the RF + PFz of the LF), MidR–L/(PFz of the RH + PFz of the LH), MidR–L/(PFz of the LF + PFz of the LH) were 94%, 91%, and 91%, respectively, whereas the accuracies of ANNs with other input variables were in the range of 55% to 63%. Use of an input of MidR for the nonaffected side of a dog or MidR–L for each side of a dog for an ANN did not yield a high accuracy. However, when the difference was normalized on the basis of the sum of the PFzs of the 2 forelimbs, 2 hind limbs, or 2 left limbs, the accuracy of the ANN was > 90%.

Accuracy of the ANNs when combinations of the variables were used as inputs was summarized **(Table 2)**. Addition of the variable MidR–L/(PFz of the RF+ PFz of the LF) to the variable MidR–L/(PFz of the RH + PFz of the LH) increased the overall accuracy to 96%. Addition of the variable MidR–L/(PFz of the LF + PFz of the LH) to the variable MidR–L/(PFz of the RF + PFz of the LF) yielded no change in accuracy from use of MidR–L/(PFz of the RF + PFz of the LF) as a single variable. When the variables MidR–L/(PFz of the RH

Table 2—Overall accuracy for diagnosis of lameness in dogs with ANNs developed by use of combinations of 3 single-input variables related to midlevel measurements obtained from GRF data.

Input			
MidR–L/ (PFz of the RF + PFz of the LF)	MidR–L/ (PFz of the RH + PFz of the LH)	MidR–L/ (PFz of the LF + PFzof the LH)	Overall accuracy (%)
X	—	—	94
—	X	—	91
—	—	X	91
X	X	—	96
X	—	X	94
—	X	X	89
X	X	X	93

— = Variable not included as input to an ANN. X = Variable included as input to an ANN.

Table 3—Overall accuracy for diagnosis of lameness in dogs with ANNs developed by use of combinations of input variables related to midlevel measurements obtained from GRF data.

Input										Overall accuracy (%)	
MidR–L/ (PFz of the RF + PFz of the LF)	MidR–L/ (PFz of the RH + PFz of the LH)	PFz of the LF	PFz of the LH	PFz of the RF	PFz of the RH	Limb unloading rate of the RF	Limb loading rate of the RH	Limb unloading time of the RF	Limb loading time of the RH	Data configuration 1	Data configuration 2
X	X	—	—	—	—	—	—	—	—	96	99
X	X	X	—	—	—	—	—	—	—	96	99
X	X	—	X	—	—	—	—	—	—	88	99
X	X	—	—	X	—	—	—	—	—	95	100
X	X	—	—	—	X	—	—	—	—	93	100
X	X	—	—	X	X	X	X	—	—	97	99
X	X	—	—	X	X	X	X	X	X	96	99

Data configuration 1 contained patterns or observations for 7 dogs, whereas data configuration 2 contained patterns or observations for 7 other dogs.

See Table 2 for remainder of key.

+ PFz of the LH) and MidR–L/(PFz of the LF + PFz of the LH) were combined, the accuracy of the ANN decreased to 89%. This was lower than when either of the 2 variables were used individually. When the variables MidR–L/(PFz of the RF + PFz of the LF), MidR–L/(PFz of the RH + PFz of the LH), and MidR–L/(PFz of the LF+ PFz of the LH) were combined, the overall accuracy of the ANN was 93%. Thus, with data configuration 1, the combination of variables that yielded the highest overall accuracy was the combination of MidR–L/(PFz of the RF + PFz of the LF) and MidR–L/(PFz of the RH + PFz of the LH). Normalizing MidR–L on the basis of the PFz of the RF + PFz of the LH, PFz of the LF + PFz of the RH, and PFz of the RF + PFz of the RH did not improve accuracy.

The preferred combination of input variables was the combination of MidR–L/(PFz of the RF + PFz of the LF) and MidR–L/(PFz of the RH + PFz of the LH). An ANN was also trained with these inputs by use of data configuration 2, and the accuracy for this evaluated data set was 99%. Accuracy of the ANN for data configuration 1 did not increase for a model with all variables considered (ie, MidR–L/[PFz of the RF + PFz of the LF], MidR–L/[PFz of the RH + PFz of the LH], PFz of the LF, PFz of the LH, PFz of the RF limb unloading rate of the RF, limb loading rate of the RH, limb unloading time of the RF, and limb loading time of the RH). The only increase in accuracy for data configuration 1 was for use of the variables MidR–L/(PFz of the RF + PFz of the LF), MidR–L/(PFz of the RH + PFz of the LH), PFz of the RF, PFz of the RH, limb unloading rate of the RF, and limb loading rate of the RH, which resulted in an overall accuracy of 97% **(Table 3)**. From data configuration 2, the accuracy increased to 100% when PFz of the RF or RH was included as a third input variable to MidR–L/(PFz of the RF + PFz of the LF) and MidR–L/(PFz of the RH + PFz of the LH).

Discussion

Data from the study reported here supported the use of ANNs as a viable computational method for GRF data to predict subjective lameness scores in dogs. These results are consistent with use of ANNs in studies[10,12–14] on the gait of humans and horses. The results for the present study are promising, considering the small number of patterns and dogs used for model development, subjective target values, and the unequal number of training patterns from each class of lameness. It is preferable to have the same number of patterns for each class of lameness for model development so that examples from each class have nearly the same influence on the ANN.[19] Analysis of the results of the present study confirmed that ANNs work well with limited canine GRF data when appropriate input variables are used.

Abnormal gait attributable to transection of a cranial cruciate ligament resulted in higher MidR for the nonaffected side of a dog, which indicated attempts of the dog to remove weight from the affected limb (Figure 3). Because trotting is a symmetric gait, the difference in magnitude of the MidR–L for each side of the dog also can be a good indicator for discriminating between classes of lameness severity. Because the magnitude of MidR and MidR–L is affected by the PFzs, MidR and MidR–L should be normalized on the basis of the sum of the PFzs of any set of limbs that can be set on the ground simultaneously (ie, 2 forelimbs, 2 hind limbs, or 2 ipsilateral limbs).

Analysis of the GRF data in the present study indicated that peak vertical, braking, and propulsive forces and associated impulses of the affected limb were lower than the preoperative values, and this result is consistent with results of other reports.[2,4,18,20–22] The decrease in the PFz of the affected limb indicated a decrease in weight bearing. The decrease in the peak braking and propulsive forces of the affected limb indicated a reduction in control of deceleration and acceleration, respectively.

Furthermore, results of the present study indicated that assessment of lameness diagnosis by use of ANNs could be a time-efficient procedure. Canine GRF data can be readily obtained simply by trotting a dog on a force plate. In addition, results of the present study indicated that data from only a few gait observations were required to obtain an accurate diagnosis and that ANNs can instantaneously interpret data when successfully interfaced with data acquisition software. Diagnosis of lameness via ANNs by use of GRF data obtained during gait analysis could be used in a clinical setting. Computerized gait analysis systems may be able to add accuracy, consistency, and efficiency for lameness evaluations in both clinical and research settings.

a. Model OR6-6, Advanced Mechanical Technology Inc, Watertown, Mass.
b. Acquire, version 7.31, Sharon Software Inc, Dewitt, Mich.
c. NeuroShell, Ward Systems Group Inc, Frederic, Md.

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