Modelling horse hoof cracking with artificial neural networks

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[1]*Department of Biomedical Sciences, Ontario Veterinary College, University of Guelph, Guelph, Ontario, Canada N1G 2W1; and* [2]*Department of Agricultural and Biosystems Engineering, McGill University, Ste. Anne de Bellevue, Quebec, Canada H9X 3V9.*

Suchorski-Tremblay, A.M., Kok, R. and Thomason, J.J. 2001. **Modelling horse hoof cracking with artificial neural networks**. Canadian Biosystems Engineering/Le génie des biosystèmes au Canada **43**: 7.15-7.22. The relationships between data on horse hoof crack damage and a number of other variables were modelled with artificial neural networks (ANNs). The latter were then used to generate estimates of hoof crack damage, the quality of these estimates determined, and the variables that were most appropriate for modelling selected. This was done with a view to the construction of computer-based expert systems that will be able to give diagnostic, as well as preventive and curative advice, for a variety of purposes. The highest-ranking ANN that was obtained would be able to support a fuzzy, four-level hoof damage differentiation scheme in an expert system. It is anticipated that system performance could be improved to support a ten-level scheme. **Keywords**: hoof cracking, artificial neural networks, horse, modelling.

Les relations entre les données sur les fissures de sabot et certaines autres variables ont été modélisées à l'aide de réseaux de neurones artificiels (RNA). Ceux-ci ont été utilisés pour prédire la gravité des fissures; on a ensuite évalué la qualité de ces prévisions et retenu les variables les plus utiles à la modélisation. Ce travail avait pour but de créer un système expert informatique polyvalent capable de poser des diagnostics et de fournir des conseils en matière de prévention et de traitement. Le RNA de plus haut niveau est compatible avec un mécanisme à logique floue permettant de différencier quatre degrés de gravité d'une fissure dans un système expert. Nous croyons pouvoir améliorer le système qui sera pourvu d'un mécanisme à dix niveaux. **Mots clés**: fissures de sabot, réseaux de neurones artificiels, cheval, modélisation.

INTRODUCTION

Hoof cracking is a problem with many horses and appears to be related to, and influenced by, a large number of factors such as the environment in which the animal lives and works, genetic and conformational predisposition, nutrition, and hoof care. Thus, hoof cracking is a complex phenomenon that occurs for many reasons in combination, and that impacts many aspects of an animal's existence. In this project, the overall goal was to find a practical and effective way to model and predict the occurrence of hoof cracking on the basis of relatively small groups of variables whose values are obtainable at low cost and with relatively little effort. The purpose of this was multifold. First, the availability of such a method would make it possible to easily assess the possibility of an individual horse actively suffering from hoof crack damage. Depending on the variables chosen, this might then be done automatically (Kok and Gauthier 1986; Gauthier and Kok 1989). Such an approach to problem detection and preliminary diagnosis is necessary, for example, for the development of automated management systems. Second, the risk of any one horse developing crack damage might be evaluated on the basis of such a model, and this could be useful for preventive decision making about a particular animal. Third, hoof crack risk might be assessed in this way for a population of animals, possibly affecting decisions about barn design and facility operation. Fourth, the effectiveness of specific treatments for hoof crack damage might be appraised and compared, and this could lead to the generation of optimal treatment suggestions. Thus, this work was carried out with a view toward the future creation of various computer-based expert systems that will provide diagnostic, as well as preventive and curative advice. Of essence here was to determine whether artificial neural networks (ANNs) might be suitable for the type of modelling required in this case, i.e., based on very wide, relatively short data sets of intricately correlated variables, typical of biosystem observation. In this project only the first purpose mentioned above was specifically addressed. The immediate project objectives were therefore: a) to examine which variables would be suitable for use in moderately-sized ANN models and, b) to determine how well the ANN models reflected the complex relationships between hoof cracking damage and various other factors.

The project was carried out in two major phases: data collection and modelling. These chronologically overlapped to some degree, so that the early part of the modelling was done with a somewhat smaller data set than the later part. In total, data were collected on 110 horses, for a very wide variety of variables related to hoof cracks, horse care, environmental conditions, animal genetics, etc. Data collection involved the interviewing of horse owners, farriers, and stable managers, as well as the taking of measurements on the animals, on their physical environments, and on their feed. Most of the data were collected during the hoof care visits of cooperating farriers. The data were stored in a combination spreadsheet/relational database, in which the values of a number of *derived variables* were also calculated. Some of the latter were simple, linear combinations of other variables, such as the difference between pre- and post-trimming toe length, whereas others corresponded in more complicated ways to measured quantities, like hoof score and horse score. The relationships between variables were then modelled by training ANNs of various architectures. To do this, the ANNs were first trained with a number of different subsets of the data, corresponding to different groups of variables, and then tested for their efficacy in reproducing the relationships between cause and effect variables (inputs and outputs). The modelling was done in two stages. In the first stage a large number of variables was tested as inputs, and the most influential and useful ones were selected. In the second stage, subsets of these *prime variables* were then tested, so as to arrive at relatively small networks in which a substantial fraction of the relationships between the data had been captured.

LITERATURE REVIEW

It appears that there is a large number of factors that can lead to, or contribute to, equine hoof defects. Some of these are inherent in the animal, such as genetic attributes; others are related to environment, care, and nutrition; yet others are associated with mechanical stresses. Accordingly, the subject of hoof damage can be studied from a perspective based on any of these factors, or any combination of them. Tyznik (1988) and Giffin and Gore (1989) were, for example, concerned about excessive dryness, leading to extraction of moisture from the hoof faster than it can be replaced. In this regard, Strasser (1998) has described how wild horses will go to a water source every day to drink, but then also will stand in it so that their hooves are re-hydrated. In many studies the focus has been on nutritional factors. Comben et al. (1984) suggested, for example, that biotin deficiency may be the cause of hoof wall defects; in more recent research on the addition of biotin to the diet of Lipizzaner horses a small but significant effect was indeed noticed (Josseck et al. 1995a, 1995b). As well, Buffa et al. (1992) have described how hoof horn growth rates and hardness improved, especially in the toe and quarters regions, after biotin supplementation. Minerals, such as calcium, are also viewed as important for hoof structure. For instance, Kempson (1987) has documented the effect of calcium deficiency, as well as the effect of a calcium: phosphorus imbalance (Kempson 1990). Yager and Scott (1985) have suggested that deficiencies of vitamin A and zinc might be causes of hoof horn defects. In an attempt to identify the roles of methionine and cysteine in hoof health, Ekfalck et al. (1990) have studied the distribution of these compounds in newly laid keratin.

Overall, the mechanisms via which hoof cracks occur are not well understood. There is evidence both from *in vivo* strain gauge experiments (Thomason 1998) and from *in vitro* photoelastic studies (Dejardin et al. 1999), as well as from finite-element modelling (Hinterhofer et al. 1997), that most of the surface of the hoof wall is usually loaded in compression. The distal border of the wall may, however, experience some horizontally oriented tension, which would explain the origin of cracks at that border. But, cracks also form at the coronary band, which appears not to be loaded in tension. The possible role of shear stresses in crack formation has not been investigated. Generally, once cracks form, the microscopic structure of the hoof wall tends to prevent them from lengthening, or it diverts them in less damaging directions (Bertram and Gosline 1986; Kasapi and Gosline 1997).

Often, models of the effects of various factors on equine physiology consist of algebraic equations in which the values of the coefficients are typically derived from the statistical analysis of data. The model of Johnson et al. (1992) in which pulmonary hemorrhage in race horses is linked to exercise is, for example, of this type. In contrast, in the work presented here, the modelling approach is based on the use of ANNs in which knowledge about relationships is encoded much more in an implicit, rather than an explicit manner. Sometimes this is advantageous. Accordingly, ANNs have been gaining favor, and are being increasingly employed in biological and biosystems applications. For instance, Lacroix et al. (1995) predicted cow performance with an ANN model. Chen et al. (1995) used ANNs to classify red wheat by analysing near-infrared diffuse reflectance spectra of ground kernels. Lacroix et al. (1999) modelled corn drying with ANNs. Lacroix and Kok (1999) created a primitive greenhouse "system consciousness" with ANNs, as part of a simulation-based controller. Suchorski-Tremblay and Kok (1997) used ANNs to model microbial acclimation in soil. ANNs have also been used for diagnosis in human medicine. In this context, Snow et al. (1994) obtained a 90% success rate in the diagnosis of prostate cancer, and Lapuerta et al. (1995) predicted the risk of coronary artery disease based on elements of the serum lipid profile. The only work to date based on ANNs in the context of hooves is that of Savelberg and Van Loon (1997). They recorded strains in the hoof wall and ground reaction forces on the hoof, and successfully reconstructed force profiles from strain patterns. With this work it was demonstrated that the hoof wall can be used as a force transducer under laboratory conditions.

Artificial neural network technology as such is well-known and described extensively in the literature. For in-depth descriptions of ANNs and their applications, the reader is referred to Haykin (1994) and NeuralWare (1995a, 1995b). The terminology used herein is as presented in NeuralWare (1995a, 1995b).

MATERIALS and METHODS

Data and data collection

Data that were directly related to the horses are referred to here as *primary data*. Two kinds of primary data were collected, the first comprising physical measurements on the animals and the environments in which they lived and worked, the second kind consisting of human responses to a set of questions. Some of the human response information was obtained from the horse owners, and some from the farriers and stable managers. *Secondary data* were collected on feed and supplement composition, the farriers, the horse owners, the stable managers, etc. Overall, the data collected were of three types: numeric, alphabetic, and binary, the corresponding variables being grouped into eight categories, some of which were divided into sub-categories. The categories are shown in Table 1, together with many of the variables that belong to each of them. It is to be noted that not all the system variables are listed in Table 1; many of the secondary variables were left out for the sake of brevity. Also, as mentioned previously, values were calculated for a number of derived variables; these were subsequently treated in the same manner as the primary and secondary data, i.e., they were stored in the same way and used for modelling, etc.

As indicated in Table 1, not all the variables for which values were collected were subsequently used in modelling; the intent at collection time was to ensure that enough data of different kinds would be available during the modelling phase, as well as during possible future work, without having to return to the source.

Table 1. Categories and sub-categories into which variables were grouped. Variables that were 'pre-selected' for modelling are shown in italics; the numbers of pre-selected variables are shown in brackets.

Category or sub-category:
A) General Information (0) date of visit, barn name of horse, stable identification & owner, farrier identification, horse owner identification
B) Horse Characteristics (7) registered name of horse, gender, birth year, dam's & sire's breed, *wither height*, girth weight, *back + neck conformation flaws*, *fore legs conformation flaws*, *hind legs conformation flaws*, back & limb injury, *hoof wear*, *gait flaw*, *movement vice*, chronic medical problem, farrier's comments on horse & on horse's care
C) Activity (10) *amount of time spent in stall during summer* & what part of the day, *amount of time spent in stall during winter*, & what part of the day, *amount of time spent in field during summer*, & what part of the day, *amount of time spent in field during winter* & what part of the day, *type of exercise performed (involving a human)*, *exercise intensity* & duration & frequency & *total time & on what surface*, frequency of bathing, type of competition & *on what surface & number per year* & over what period
D) Environment of the Containment Space (11) **a) stall or shed or field** (6): large space's temperature & relative humidity, ceiling type, space type & length & width & height, gross ventilation area of space & ventilation obstruction type, *flooring type & at surface dry/wet* & drainage system, *bedding type & at surface dry/wet & depth* & temperature & relative humidity *& NH_3 concentration*, type & height off the floor of water & grain & hay containers **b) field/paddock** (1): length, width, *footing type* & texture, surface covering, frequently wet areas **c) exercise/work 1 & 2** (2*2): type, length, width, *footing type & depth* & texture, relative humidity, surface covering
E) Nutrition (13) **a) water** (1): source, *hardness*, amount consumed **b) grain 1 & 2, mix feed 1 & 2** (4*1): *type*, manufacturer, product name, daily amount fed, number of feedings **c) specialty feed** (1): *type*, manufacturer, product name, daily amount fed, number of feedings, how long given **d) hay** (1): *grasses*, format fed, bale size, flake mass, daily number of flakes, number of feedings **e) pasture** (1): *grasses*, duration of use, duration of hay supplementation **f) salt** (1): present, *type + format*, container, consumption **g) supplements 1 & 2** (2*1): *type*, manufacturer, product name, daily amount fed, how long given & for what reason **h) treats** (1): *type* **i) worming medicine** (1): *products*, frequency administered **j) dentistry** (0): annually checked
F) Hoof Care (43) **a) general** (7): *frequency of farrier visits, hoof sealer & conditioner application, hoof treatment 1 & 2, farrier treatment for front shoes* & *hind shoes* **b) per hoof** (4*9): *overall wall quality, shape, wall colour, pre- & post-trim toe length & toe angle, wall thickness (wall + white line) at toe*, inside and outside quarters, *known history* **c) shoes front & rear** (2*0): brand, size, length behind heel (right & left), material, shape, purpose, insert & wedge & pad & add-on, material, purpose, nails: brand & size & number used & placement & height of clinch per shoe
G) Relatives (0) sire's name & famous lineage & number of generations to subject, dam's name & famous lineage & number of generations to subject, names of up to 6 full + half siblings & names of up to 6 offspring
H) Hoof Cracks (up to 4*7=28) *number of cracks per hoof, up to six cracks (each crack's length* & location on hoof)

Whenever possible, more than one horse was examined at any one stable. All the stables at which data were collected were located in the province of Ontario. A total of 37 stables were visited, 20 in the eastern region and 17 in the southwestern region. A total of 110 horses were examined, the majority being of the "backyard" type, meaning they were primarily pleasure mounts, or pets. The rest were active sporting horses. The animals that were included in the sample were selected so that the hoof cracking data would be "balanced" for ANN training, i.e., a wide range of hoof cracking damage levels needed to be present, but fairly evenly distributed. Thus, the animals included in the sample were not chosen entirely randomly from the population available, so that the statistics obtained for average hoof cracking etc. are therefore not statistically representative of that population - these are also not reported here. No other selection criteria were applied. Of the animals in the sample, about 25% did not have significant hoof cracks at all, i.e., 0-3 mm in length, and the rest had at least one crack 4 mm in length, or longer. Nine farriers cooperated in the study, seven in the eastern Ontario region and two in the southwestern region.

The measured data were obtained as follows: temperature and relative humidity were determined with a thermo-hygrometer (Thermor, Markham, ON). Ammonia concentration at the bedding surface was quantified with detector tubes hooked up to a gas pump (1 to 30 ppm #3L tubes, and a GV100S pump, both from Gastec, Kanagawa, Japan). Lengths were measured with a standard 6 m steel tape. Feed masses were obtained with a kitchen balance (5 kg ± 25 g, Sunbeam), and a spring scale (5 kg, Ohaus) to which a feed bag had been attached that was used as a sack. Hoof and horse data were taken with a hoof gauge (for toe angles), a caliper and a 300 mm stainless steel ruler (for the lengths of the toes and the hoof cracks), and a horse and pony height and weight tape (Coburn, Whitewater, WI).

Hoof and horse scoring

The cracking damage was assessed on the basis of the physical measurements that had been taken on each of the animals' hoofs. Since up to six crack lengths were recorded for each hoof, i.e., up to 24 data values per animal, it was necessary to formulate some composite measures so as to reduce the number of variables that had to be dealt with. Accordingly, a number of derived variables were defined and values calculated for these. First, for each hoof, a *hoof score* was calculated from the individual crack lengths and then, for each animal, a *horse score* was calculated from the four hoof scores. The horse scores were then used in the modelling. Both hoof and horse scores were scaled from 0 to 9 and are dimensionless.

For the hoof score, the crack lengths were combined in such a way as to reflect an approach that would probably not be unlike that taken by a human in a judgment situation. This is reflected in:

$$Hoof\ \ Score = 9\tanh\left[\frac{c_1 + \frac{c_2}{2} + \frac{c_3}{3} + \frac{c_4}{4} + \frac{c_5}{5} + \frac{c_6}{6}}{50}\right] \quad (1)$$

where: c_1, c_2, etc. = crack lengths arranged from maximum to minimum (mm).

This always resulted in an acceptable hoof score value. For example, for horse 76, there were three cracks in the right hind hoof, whose lengths were respectively 75, 30, and 13 mm. For this case, the equivalent total crack length was 94.3 mm, and the hoof score was 8.6. Also, use of Eq. 1 resulted in reasonably flat distributions of hoof scores and horse scores, which was desirable for ANN training.

Horse scores were derived from the hoof scores according to:

$$Horse\ Score = 9\tanh\left[\frac{\left(h_1^3 + h_2^3 + h_3^3 + h_4^3\right)^{1/3}}{9}\right] \quad (2)$$

where: h_1, h_2, etc. = hoof scores.

Neural network modelling

The software used was NeuralWorks Professional II/PLUS (NeuralWare Inc., Pittsburgh, PA). All the ANNs that were used were of the feedforward, fully-connected type. They all had two hidden layers, and the number of PEs in each of these was always 2N+1, where N is the number of inputs. Networks are described in terms of the numbers of PEs in their layers, e.g., 6-13-13-1. The supervised back-propagation learning method was used, based either on the Delta learning rule or on the Normalized Cumulative Delta learning rule; the first of these was employed during stage 1, and the second rule for stage 2 of the modelling. For all experiments, networks were trained for 50,000 cycles. The effect of the various inputs on ANN performance was tested directly, as well as indirectly, as well as with a combination approach.

As mentioned previously, the modelling was done in two stages. In the first stage, groups of pre-selected variables from the different categories were used as network inputs, and it was attempted to determine which ones amongst them were the most powerful for predicting hoof damage. The indirect and direct methods of influence determination were used in tandem in this procedure. Overall, this resulted in the selection of a set of twenty-two prime variables. In the second stage subsets of different widths, ranging from five to eight variables, were tested as network inputs in full factorial experiments, to identify which combinations had the highest predictive capacities.

As indicated in Table 1, for several categories no variables were pre-selected at all, and in each of the other categories only a limited number were pre-selected for stage 1 modelling. A number of experiments were then carried out for each of the categories of variables, the number of experiments depending on what inputs, or combinations of inputs, were removed for the determination of the influence of the individual variables. For example, for the variables related to horse characteristics, a total of 29 experiments were run, corresponding to all combinations of no inputs removed, and of one, and two inputs removed in combination - this corresponds to the direct method of influence determination. Similarly, 56 experiments were run for the variables related to activity, etc. In total, 195 stage 1 experiments were done.

For each stage 1 experiment, an ANN was trained and then its recall performance was evaluated, first with none of its input PEs disabled, and then with each of its input PEs disabled in turn, this latter procedure corresponding to the indirect approach to influence determination. Thus, as mentioned above, the direct and indirect methods were used in tandem in this case. When no input PEs were disabled, the correlation coefficient between the known output values in the training set and the output values obtained from the ANN during recall was calculated and then used as the measure to evaluate the networks' learning achievement. The probability of significance as per the Student's t-test was also calculated for these. Thus, 195 of these were calculated, 29 of them specifically related to horse characteristic variables, etc.

Corresponding to the ANN software's capacity for PE disablement, it could also generate values of *percent impact* for each of the input variables. This is a relative measure. Variables were then judged on the basis of a number of factors including the correlation coefficients and the average impact values obtained for them; ultimately twenty-two prime variables were chosen.

For stage 2 modelling, 110 data records were available, with a total of 22 prime input variables, with the horse score again as

Table 2. Five largest correlation coefficients obtained for Stage 1 experiments for two categories of variables, in order of decreasing value.

Category of variables	Input variables used	Correlation coefficient
Horse characteristics	all inputs	0.8568
	all, less back + neck & fore legs conformation flaws	0.8288
	all, less back + neck conformation flaws	0.7835
	all, less back + neck conformation & gait flaw	0.7704
	all, less gait flaw & movement vice	0.7687
Activity	all, less number of competitions per year	0.7392
	all, less exercise surface	0.7372
	all, less total time exercise & competition surface	0.7350
	all, less total time exercise & summer field time	0.7239
	all inputs	0.7228

the sole output variable. In stage 2, ANN performance was evaluated both with the training set and with data to which the network had not been exposed previously - the *witheld* set. To do this in a balanced manner, for each experimental run, 10 records were chosen randomly and withdrawn from the data set and kept apart, while the network was trained with the other 100. This was repeated independently 25 times for each experiment so that for each stage 2 experiment an ANN was trained and evaluated with 25 different data sets.

In stage 2 modelling, ANN performance was evaluated exclusively on the basis of the correlation coefficient between a network's known and recall output values. These were calculated as for stage 1, again, together with their probability of significance as per the Student's t-test. However, in this case, correlation coefficients were calculated both for the training and for the withheld data sets. Thus, for each experiment a matrix of 25x2 correlation coefficients was obtained. The averages and standard deviations of these were then computed, and an overall *experiment score* derived from them using:

$$Experiment\ Score = \frac{0.5Rt_{avg} - 0.15Rt_{std} + 1.0Rw_{avg} - 0.35Rw_{std}}{1.5} \qquad (3)$$

where:

Rt_{avg},Rw_{avg} = averages of the 25 correlation coefficients obtained for the training and withheld data sets, respectively, and

Rt_{std},Rw_{std} = standard deviations of the 25 correlation coefficients obtained for the training and withheld data sets, respectively.

The stage 2 experiments were carried out in four series, corresponding to the number of input variables used. First, for series 1, a full factorial set of experiments was done in which each of the networks had five inputs. Therefore, a total of 26,334 experiments were completed, each consisting of 25 experimental runs with networks that had a 5-11-11-1 architecture. The experiments were then ranked according to their scores and the 100 most successful sets of five variables were retained for the next series. Then, in series 2, each of the sets of five variables was combined with each of the remaining 17 variables in 1700 more experiments in which the ANNs had 6-13-13-1 architectures. Next, the best 100 sets of six variables were combined in series 3 with the remaining 16 variables, etc.

RESULTS and DISCUSSION

Stage 1 modelling

Some of the correlation coefficients obtained for the stage 1 experiments are presented in Table 2. For all of these the probability of significance as per the Student's t-test was greater than 99.9%. In most cases the differences among the top five coefficients for a category were quite small and the maximum values were generally not obtained for the largest number of variables. Overall, indirect method testing indicated that similar modelling results could be obtained with very different sets of input variables, and that none of the variables had an overbearing influence on the outcome. This is a common situation for a wide set of highly correlated variables; it has the advantage that any variable which is not convenient to measure can be left out of the model without undue impact, and the disadvantage that it is not very evident which variables to use. The choice of prime variables was therefore also based on their

Table 3. Selected average percent impact values obtained for input variables.

Category (no. values averaged)	Variable name	Ave. percent impact
Horse Characteristics:	wither height	48.0
No. variables 7	back + neck conformation flaw	74.2
No. variables shown 7	fore legs conformation flaw	50.3
Impacts shown are	hind legs conformation flaw	43.4
averages of 22 values	gait flaw	60.0
	movement vice	72.8
	hoof wear	68.9
Activity:	exercise type	61.6
No. variables 10	total time for exercise	51.6
No. variables shown 5	exercise surface	56.3
Impacts shown are	competition surface	46.9
averages of 46 values	no. competitions	57.5
Environment:	flooring surface dry/wet	55.1
No. variables 11	bedding surface type	40.6
No. variables shown 5	exercise/work space1 footing surface	67.3
Impacts shown are averages of 56 values	exercise/work space2 footing surface	56.5
	field/paddock footing surface type	89.4

Table 4. Variables selected for stage 2 modelling (the *prime variables*).

Category	Variable name	Variable number
Horse characteristics	back + neck conformation flaws	1
Horse characteristics	hind leg conformation flaws	2
Horse characteristics	movement vice	3
Activity	time spent in stall during summer	4
Activity	time spent in stall during winter	5
Activity	time spent in field during summer	6
Activity	time spent in field during winter	7
Activity	competition surface type	8
Activity	number of competitions per year	9
Environment	flooring surface dry/wet	10
Environment	bedding surface type	11
Environment	footing type in exercise/work space 1	12
Environment	footing type in exercise/work space 2	13
Environment	field / paddock footing surface type	14
Nutrition	grain type 1	15
Nutrition	grain type 2	16
Nutrition	specialty feed type	17
Nutrition	supplements type 1	18
Nutrition	supplements type 2	19
Hoof care	hoof sealer application	20
Hoof care	hoof conditioner application	21

Table 5. Experiment scores obtained in stage 2 modelling; best three results are shown for each of the four series.

Series	Rank									Score
1	1				3	4	11	13	17	0.586
1	2				3	4	11	17	21	0.578
1	3				3	6	11	13	17	0.573
2	1			3	4	11	17	21	22	0.616
2	2			3	4	14	17	21	22	0.606
2	3			3	6	14	17	21	22	0.606
3	1		3	4	9	11	14	17	21	0.662
3	2		3	4	8	11	14	17	21	0.652
3	3		3	4	11	13	14	17	21	0.650
4	1	1	3	4	11	13	14	17	21	0.694
4	2	3	4	8	9	11	14	17	21	0.664
4	3	3	4	11	13	14	17	19	21	0.664

average percent impact. A number of these values are presented in Table 3. The twenty-two prime variables that were then selected are listed in Table 4 in which they are also assigned *variable numbers*, by which they are subsequently referred to for the reporting of stage 2 modelling results.

Stage 2 modelling

The three highest ranking input variable combinations for each of the four series of stage 2 experiments are presented in Table 5. For all the correlation coefficients from which the scores were calculated the probability of significance as per the Student's t-test was greater than 95%. As is evident from the values in the table, each addition of an input variable resulted in a substantial improvement in the score. Overall, the change from five to eight inputs resulted in an 18% improvement. The highest score that was attained was 0.694, with an 8-17-17-1 network.

During the stage 2 experiments it became evident that some variables occurred relatively often in the inputs combinations of highly ranked networks. Variables 3 (movement vice), 4 (time spent in stall during summer), 11 (bedding surface type), 14 (field/paddock footing type), 17 (specialty feed type), and 21 (hoof conditioner application) all occurred more than 75 times in the top 100 ranked networks. It is noteworthy that between these six variables all five categories from which prime variables were drawn are represented, i.e., a combination of factors from all categories seems to be the most highly predictive. The overall winning combination with eight inputs also contained variables 1 (back + neck conformation flaws) and 13 (footing type in exercise/work space #2). Of these, variable 13 occurred fairly frequently in other highly-ranked networks, especially in the narrower ones, but variable 1 occurred much less frequently.

To give a more complete illustration of the highest-ranked network's performance, typical training and withheld data sets of 100 and 10 records, respectively, were created de novo by randomly choosing records, and the ANN was trained for 50,000 cycles as usual. Predicted horse scores were then obtained by recalling, with both sets. The results are presented in Figs. 1 and 2, where they are plotted vs the known horse scores. Of course, under ideal circumstances all the points would fall on the diagonals, which are also shown on those graphs. The correlation coefficients for these two situations were respectively 0.891 and 0.666. For this particular data set, for the training data, there was an average difference between the real and the predicted horse scores of 0.98 (standard deviation 1.06); for the withheld set this difference was 1.57 (standard deviation 0.98). These statistics were quite representative of the situation.

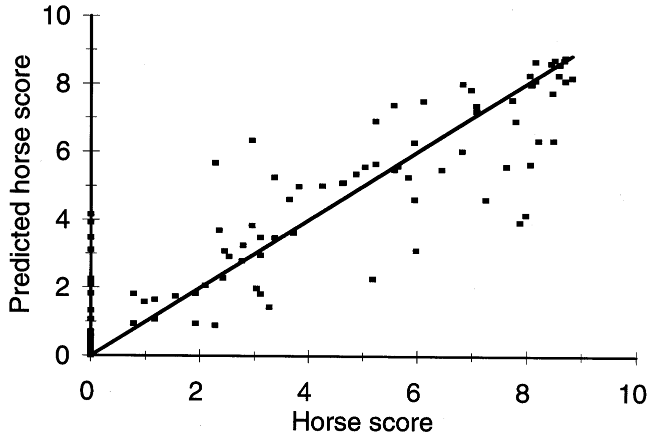

Fig. 1. Performance of the highest-ranked eight-input ANN on its training data.

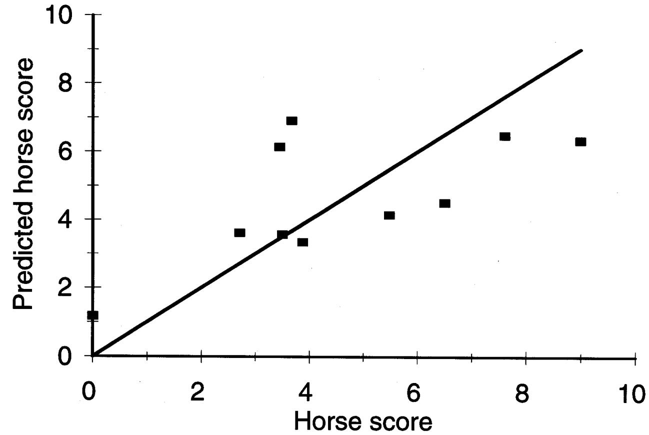

Fig. 2. Performance of the highest-ranked eight-input ANN on the withheld data.

Although in Fig. 1 it appears that the network doesn't perform very well when the actual horse score is zero, i.e., with no hoof cracking at all, on the average the error in the score that is obtained is not substantially larger than for the other data points. Thus, for these instances the average predicted horse score is 1.10 (standard deviation 1.29). Overall, on the basis of the combination of the eight input variables chosen, and with this type of network and training approach etc., for animals not included in the training set, the horse score can be predicted within approximately 2.5 points about 65% of the time, i.e., within one standard deviation of the mean difference between real and witheld sets. Based on this, a fuzzy, four-level classification scheme could be implemented, and the results accepted with reasonable confidence.

CONCLUSIONS

The overall goal of the project was to find a practical and effective method to model and predict hoof cracking on the basis of relatively small groups of variables whose values are obtainable at low cost and with relatively little effort. This goal was established for a number of purposes, and artificial neural network technology was examined as the prime candidate for the modelling work.

Reasonable progress was made towards the overall goal, and the project was deemed rather successful, especially because it was a first attempt at modelling this situation with ANNs. The results were also encouraging in a wider context in that they support the position that it is quite feasible to model very complex, wide data sets derived from biological systems with fairly narrow ANNs (see also Lacroix et al. 1995). The success of this approach depends partly on a judicious choice of variables, together with their combination into group representatives, as well as the establishment of relevant performance criteria. Accordingly, in the project, variables were combined into scores, and performance evaluation was based on impact and correlation measures. In this case, the most influential variable was "movement vice", a binary variable. It is not difficult to envisage how its value might be determined automatically with good certainty, so that its inclusion for the purpose of assessing an individual animal's hoof damage level is easily justified. However, for some of the other purposes, this might not be so. Thus, the selection of input variables must always be partially based on the specific purpose of modelling.

The precise quantitative description of hoof cracking damage is difficult at best, and one would normally expect answers in terms of fuzzy, natural language descriptors such as "hardly damaged at all", "severely damaged", etc. (see Lacroix et al. 1998). In this regard, the predictive capacity of the highest-ranking network is presently adequate to fairly dependable in producing ratings in terms of a four-level descriptor set. When combined with fuzzy reasoning mechanisms, this is quite sufficient to make a useful management contribution. Analysis and advice generation could be done in a completely automated manner or could take place via a user interface (see Kok and Gauthier 1986; Gauthier and Kok 1989). It is felt that it would not be very difficult to improve ANN performance so as to be able to clearly differentiate between about eight to ten levels of hoof damage.

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