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Performance of an artificial neural network for vertical root fracture detection: an *ex vivo* study

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Abstract – *Aim*: To develop an artificial neural network for vertical root fracture detection. *Materials and methods*: A probabilistic neural network design was used to clarify whether a tooth root was sound or had a vertical root fracture. Two hundred images (50 sound and 150 vertical root fractures) derived from digital radiography – *used to train and test the artificial neural network* – were divided into three groups according to the number of training and test data sets: 80/120,105/95 and 130/70, respectively. Either training or tested data were evaluated using grey-scale data per line passing through the root. These data were normalized to reduce the grey-scale variance and fed as input data of the neural network. The variance of function in recognition data was calculated between 0 and 1 to select the best performance of neural network. The performance of the neural network was evaluated using a diagnostic test. *Results*: After testing data under several variances of function, we found the highest sensitivity (98%), specificity (90.5%) and accuracy (95.7%) occurred in Group three, for which the variance of function in recognition data was between 0.025 and 0.005. *Conclusions*: The neural network designed in this study has sufficient sensitivity, specificity and accuracy to be a model for vertical root fracture detection.

Early detection of vertical root fracture can prevent extensive damage to supporting tissue. The diagnosis of vertical root fracture is based on the clinical signs and symptoms and radiographic demonstration of a fracture line. There have been attempts to increase the diagnostic accuracy of radiographic methods by moving from conventional radiography to digital imaging and the use of digital image enhancement (1, 2). The performance of 2-dimensional (2D) conventional vs manipulated digital radiography has not, however, provided a significant benefit (1–3). In fact, the diagnostic value of 3-dimensional (3D) images (such as CT or cone-beam CT in detection of vertical root fracture) was higher than that of 2D images (4–6). Notwithstanding, high radiation exposure, high cost, metal artefact and lack of availability may limit or argue against the extended use of 3D. The diagnostic performance of these radiographs depends on the capability of images in presenting the fracture line and of the observers in detecting that fracture line. The validity and repeatability of diagnostic outcomes are influenced by the experience of the observers. The lack of diagnostic methods to increase the effectiveness of clinical and radiographic evaluation *for the diagnosis of vertical root fractures* compelled us to look for a new method, which is relatively inexpensive for a developing nation, not complicated, and does not increase the radiation dose, for root fracture detection.

An artificial neural network is a mathematical model that emulates the brain's operation. It consists of a variable number of small, computing elements (termed neurons), which are each able to perform a single mathematical function. Each neuron has one or more inputs – such as input data to the network or connections from other neurons in the network (termed synapses). The signal (collected data) from the connecting neuron over that synapse can be represented by a weight between 0 and 1. The total input to the neuron is the summation of these weighted inputs for all of the synapses to the neuron. The output from each neuron (known as 'activity') is derived by processing the total input to the neuron through a mathematical algorithm (called the transfer function). The overall structure of the network is called 'architecture'. A typical neural network has an input layer (or level) consisting of one or more neurons for each input variable (e.g. age of the patient), which send data via synapses to the second layer or intermediate 'hidden' layers that do not connect directly to either inputs or outputs, and an output layer – which has one or more neurons giving a graded output which is the output of the network. The more complex the system, the more layers of neurons it will have (7).

Artificial neural networks, following training, are able to discriminate important patterns in input information and respond with an appropriate output (8). Thus, a neural network possesses a number of features suitable for diagnostic work (9, 10), but its utility in root fracture diagnosis has not yet been demonstrated.

The purpose of this study was to design a neural network for the diagnosis of vertical root fractures using images from intraoral digital radiography and evaluate the diagnostic performance of the neural network, including the effect of alteration in function distribution for vertical root fracture detection.

Materials and methods

Tooth preparation

We used 200 extracted human premolar teeth, which had a single root, no dental caries and no endodontic filling material. The teeth were stored in formalin, rinsed in tap water, carefully cleaned with a toothbrush and dried before fracture line preparation. The crowns were removed 2 mm from the cemento-enamel junction with a taper-shaped diamond bur and each remaining root fixed in an acrylic box. The teeth were numbered and then divided into two groups. Roots with and without a created fracture line comprised 150 and 50 teeth, respectively. Each root was coated with a layer of wax approximately 1 mm thick and fixed in an acrylic block. A vertical root fracture was induced as described by Monagham et al. (11). A conical wedge with a 60º bevelled tip attached to the universal testing machine was apically driven into the tooth. The universal testing machine automatically stops if the root cracks. The force used to produce root fracture ranged between 79 and 657 N.

The study conformed to the Helsinki Declaration, and The Ethics Committee at Khon Kaen University approved the study (HE532241).

Radiographic procedure

All radiographic exposures were made with an RVGui sensor (Trophy, Beaubourg, France) in the facio-lingual direction using a parallel technique then saved in TIFF format before being converted to BMP files (horizontal and vertical resolution was 1302 dpi–width 1024 pixels and height 1536 pixels). The digital X-ray unit (Novelix; Trophy), with a round collimator, was operated at 65 kVp and 8 mA for 0.08 second. The focus object distance was 24 cm, and the object to receptor distance was 1 cm.

Neural network design

Developing a neural network begins with the design of a neural network architecture and is followed by training the neural network. The final phase is validation. We designed a probabilistic neural network, which comprises two layers (Fig. 1): the first was the input layer, which included a radial basis layer. The transfer function was Radbas, which is a Gausian function; $f(x) = e^{-x2}/\sigma^2$ (σ was the variance of function). The result of this layer showed the curve as bell-shaped curve, of which the spread of curve was controlled by the variance of function. Data for input variable were derived from the grey-scale data, drawing line through the digital image, either normal or vertical root fracture image. The result of the Radbas was input into the next layer. The second was a competitive layer, where the transfer function was compet (C). The result in this layer was divided into two classes, *viz*. the teeth with or without a root fracture.

Training and test neural network

The artificial neural network was trained using data from digital image (numerical value) and validated using another similar set. Each digital image – *either sound or fractured tooth* – was drawn with a line passing through the root. Forty data points of grey scale per line were measured and processed to determine the prominent features of the digital image. Three lines per root were used for training data and 1 line for the unseen data (i.e. data used to test performance of neural network after having trained the neural network with training data). The total data ranged between 14 400 and 18 400 data points according to the experimental group; Group 1, training data = 80 and test data = 120, provided the lowest data points (14 400), while group 3, training data = 130 and test data = 70, provided the highest data points (18 400). These data were normalized to reduce the grey-scale variance before inputting data into the artificial neural network. The experimental groups were classified according to the number of trained and tested data used (Table 1). Each group included both fractured and nonfractured roots, and each group was assessed by determining the variance of Gausian function (σ) in recognition data between 0 and 1. The model of the root fracture diagnosis was presented as a graph on a graphic user interface (GUI) screen. Figure 2 is a GUI from the Matlab

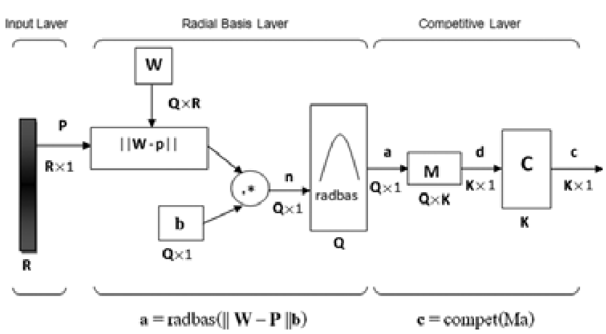

Fig. 1. Probabilistic neural network scheme. **P** vector of input variable, **R** number of input variables, **W** matrix of weight variable, **Q** vector for training, **b** bias value, **n** vector of input variable in radial basis, **a** vector of output variable in radial basis, **M** matrix of weighted variable in competitive layer, **d** vector of input variable in competitive layer, **k** the number of classes (fractured and nonfractured), **c** vector of output variable in competitive layer.

Table 1. Number of training and test teeth

Group	Training data (roots)		Test data (roots)		Total (roots)
	Fractured	Non-fractured	Fractured	Non-fractured	
1	50	30	100	20	200
2	75	30	75	20	200
3	100	30	50	20	200

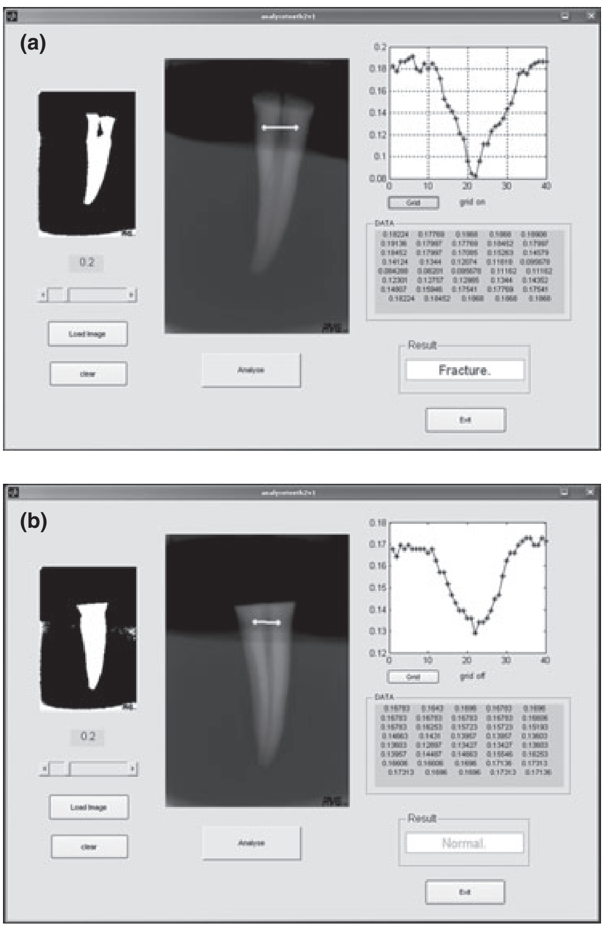

Fig. 2. (a) Graphic user interface (GUI) for root fracture diagnosis; (b) GUI for nonfractured root diagnosis.

program showing how we inserted the input picture, drew the horizontal line and received 40 data points as shown in x- axis and grey-scale data in *y*-axis, and the resulting interpretation as to whether it was a normal or fractured root. The graph in Fig. 2a, showing root fracture, differed from the graph of sound root in Fig. 2b.

Statistical analysis

The performance of the neural network was evaluated by diagnostic values (i.e. sensitivity and specificity). The sensitivity represents the performance of the neural network in detecting the appearance of the fracture line. The specificity represents the performance of the neural network in correctly identifying nonfractured roots.

Results

We prepared three groups of samples, according to the number of roots used for the initial training and testing phase. The results generally indicate that the greater the number of training roots, the greater the accuracy in diagnosis. Tables 2, 3 and 4 show the sensitivities, specificities and accuracies of the test data with a variance of the function from 0.005 to 1 in the three experimental groups. Group 1 – comprising 80 training data sets and 120 test data sets – showed the highest sensitivity (97.8), specificity (60.0) and accuracy (88.3) under the variance of function at 0.05. Group 2 – comprising 105 training data sets and 95 test data sets – had the highest diagnostic performance [highest sensitivity (97.2), specificity (78.3) and accuracy (92.6)] for the variance of function of 0.025 and 0.01. Group 3 – comprising 130 training data sets and 70 test data sets – showed the highest diagnostic performance [sensitivity (98.0), specificity (90.5) and accuracy (95.7)] for the variance of function of 0.025, 0.01 and 0.005. Comparing the accuracy among the three groups, an increase in the number of training data (i.e. Group 3 had more training data than Group 2, and Group 2 had more than Group 1) will make the neural network model more accurate in discerning root fracture. Table 5 summarizes the highest diagnostic performance of each group under the optimum variance of function. Group 3 – which had the most training data – had the highest accuracy as per the variance of function of 0.025–0.005. According to the data in Groups 2 and 3, the narrower the variance of function, the higher the recognition performance. In the current study, a variance of function of 0.5 provided the lowest specificities (0.00) for detecting nonfractured roots in three groups.

Discussion

We developed an artificial neural network model in order to increase the capability of digital images to reveal vertical root fracture.

Theoretically, the design of a neural network depends on the diagnostic needs of the user. We chose

Table 2. Sensitivity, specificity and accuracy of test data by neural network in Group 1 (training data = 80, test data = 120)

Variance of function	Fx* (n = 100)	Non-Fx* (n = 20)	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	45	19	97.8	25.7	53.3
0.5	100	0	83.3	0.0	83.3
0.25	81	14	93.1	42.2	79.2
0.1	78	17	96.3	43.6	79.2
0.05	88	18	97.8	60.0	88.3
0.025	91	12	91.9	57.1	85.8
0.01	90	14	93.8	58.3	86.7
0.005	89	16	95.7	59.3	87.5

*Fx = Fractured.

Table 3. Sensitivity, specificity and accuracy of test data by neural network in Group 2 (training data = 105, test data = 95)

Variance of function	Fx* (n = 75)	Non-Fx* (n = 20)	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	68	18	97.1	72.0	90.5
0.5	75	0	78.9	0.0	79.0
0.25	74	4	87.2	80.0	82.1
0.1	67	18	97.1	69.2	89.5
0.05	69	18	97.1	75.0	91.6
0.025	70	18	97.2	78.3	92.6
0.01	70	18	97.2	78.3	92.6
0.005	70	18	97.2	78.3	92.6

*Fx = Fractured.

Table 4. Sensitivity, specificity and accuracy of test data by neural network in Group 3 (training data = 130, test data = 70)

Variance of function	Fx* (n = 50)	Non-Fx* (n = 20)	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	48	16	92.3	88.9	91.4
0.5	50	0	71.4	0.0	71.4
0.25	50	0	71.4	0.0	71.4
0.1	45	19	97.8	79.2	91.4
0.05	46	19	97.9	82.6	92.9
0.025	48	19	98.0	90.5	95.7
0.01	48	19	98.0	90.5	95.7
0.005	48	19	98.0	90.5	95.7

*Fx = Fractured.

to design a probabilistic neural network because of its ability to accommodate training data more quickly and easily than other network designs. Moreover, a probabilistic design is known for its accuracy and noise resistance; its suitability for work needing classification, as in our study on classifying tooth roots into fractured and nonfractured groups.

The sensitivities, specificities and accuracies of the neural network vary according to the variance of function in recognition data. The highest diagnostic performance of Group 3 had the most training data and a narrow variance (0.0025–0.005). The implications are that (a) the higher the number of subjects for training the neural network, the greater its accuracy for an unknown object test; and (b) the narrower the variance of function in recognition data, the higher the number of correct diagnoses.

Compared with other techniques for detecting root fractures, cone-beam CT showed sensitivity and specificity in detecting vertical root fracture in clinical study were 88% and 75%, respectively (12). Compared with digital radiography, cone-beam CT scans are more accurate in detecting 0.2-mm vertical root fracture (70%) and 0.4-mm vertical root fracture 90%) than digital radiography (43.3% and 60%, respectively) (13). The respective sensitivity and specificity of conventional intraoral radiography in detecting vertical rot fracture were 38% and 87%, whereas by digital radiography it was 48% and 89% (14). The artificial neural networks therefore provided greater sensitivities (97.2–98.0%) and comparable specificities (60.0–90.5%) for detecting vertical root fractures.

A limitation of our study was the use of premolar teeth, with a single root and no endodontic filling material or radiopaque post. Thus, before extending our results to a clinical application, further research is needed into all known types of presentations. For example, the grey-scale data in the experimental root fracture without any radiodensity material certainly differ from the variety of root canals in clinical cases. Studies into the effect of endodontically and prosthetically treated teeth on diagnostic ability of radiographic methods have been carried out (15, 16), so we need to assess whether radiopaque material in the root canal affects the diagnostic accuracy of neural network.

The fracture space between the two fragments is a factor, which affects the accuracy of diagnostic methods. Digital radiography was unsuccessful in determining 0.2-mm vertical root fracture (13) owing to limitation of visibility. Artificial neural networks make use of grey -scale data from digital images, which facilitates interpreting root fracture.

In clinical practice, the unaided eye is insufficient and subjective. Intra-oral digital images offer advantages over the cone-beam computed tomography in that there are no streak artefacts. Radiopaque materials, such as gutta percha cones, create streak artefacts in cone-beam computed tomography that mimic fracture lines (15). Thus, the advantage of digital image over conventional radiography is image enhancement, albeit the zoom function, sharpness, pseudo-3D and inverted images do not add value for diagnostic outcomes (1–3). Tsesis et al. (14) observed that the sharpness tool made a root canal appear like a fracture line, revealing the limitation of the digital image and the observer's visibility including skill and experience in diagnostic accuracy. By contrast, a neural network can make use of grey-scale data, from which the quality of an image can be quantified through image processing. Therefore, it may provide a more objective (less subjective) alternative for root fracture detection in the future.

Table 5. Highest diagnostic accuracy of each group

Group	Variance of function	Number of test data		Number of correct diagnosis		Sensitivity (%)	Specificity (%)	Accuracy (%)
		Fx	Non-Fx	Fx	Non-Fx			
1	0.05	100	20	88	18	97.8	60.0	88.3
2	0.025–0.005	75	20	70	18	97.2	78.3	92.6
3	0.025–0.005	50	20	48	19	98.0	90.5	95.7

In this study, false positives occurred according to the difference in the shape and density of the maxillary and mandibular premolar tooth being examined. Teeth with deep grooves at the proximal surface may simulate grey-scale data similar to a root fracture detected in grey-scale.

In conclusion, artificial neural networks may become important decision-making tools. Our study indicates that an artificial neural network can be trained to make correct interpretations of root fractures. A neural network model such as that used in this study could be a prototype for root fracture detection and should be improved by expanding its application to all possible types of root fractures in clinical practice.

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Conflict of interest statement

The authors have no conflicts of interests.

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