THE USE OF ARTIFICIAL NEURAL NETWORKS TO PREDICT OSTEOPOROSIS

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R.F. HARRISON, R.L. KENNEDY[1] & R EASTELL[2]

Summary of Aims

Osteoporosis arises when the bones lose sufficient mineral to allow fractures to develop after only minimal trauma. It is an extremely common condition in post-menopausal women, and is becoming more common because of the increasing number of elderly women in the population. The most devastating effects of osteoporosis arise when the patient fractures either the hip or the vertebrae. These conditions are painful and disabling and are frequently the precipitating factor for an elderly person having to give up an independent existence. The cost of treating the results of osteoporotic fractures is immense. We now have accurate and widely applicable methods for measuring the bone mineral density, and thus identifying patients at risk. However, the necessary scanners are not widely available and it is not thought to be profitable to screen the entire population at risk with bone scanners. Once established, osteoporosis cannot be effectively treated. There is now, however, a number of treatments which effectively retard the progression of the condition if it can be identified in the early stages. These risk factors and lifestyle factors are easy to collect and could be used to identify patients who are at risk of osteoporosis and those who should have a bone scan to quantify bone mineral density. Standard statistical methods have been used in an attempt to combine these factors into a risk score. Only limited success has been obtained to date. The aim of this project was to exploit the pattern-recognition powers of artificial neural networks to identify patients at risk of osteoporosis from known risk and lifestyle factors. Neural networks are computer programs which use a large number of simple, richly interconnected processors to process data in a manner analogous to the brain. They have been applied to data from a range of medical conditions and show considerable promise. Our own work using artificial neural networks to predict diagnosis and outcome in chest pain patients is at an advanced stage.

Patients and Methods

The data for this project was obtained from Dr. R. Eastell, Department of Medicine, The University of Sheffield. Extensive data on risk factors and lifestyle, along with bone mineral density measurements, were obtained from 375 women selected at random from Sheffield General Practices. These data were examined and configured for the neural network experiments using Microsoft Excel. The data which were used are shown in Table 1.

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[1]Department of Medicine, The University of Edinburgh
[2]Department of Human Metabolism and Clinical Biochemistry, The University of Sheffield

Table 1: Clinical data used in neural network experiments

Age	Prolonged amenorrhoea
Height	History of ovariectomy
Weight	Use of hormone replacement therapy
History of thyroid disease	Pregnancy
History of diabetes	Breast feeding
Previous fractures	Smoking history
Family history of osteoporosis	Alcohol intake
Prolonged bed rest	Activity
Steroid therapy	History of height loss
Use of the oral contraceptive	
Age at menarche	

The data were coded as binary variables for neural network experiments which were conducted using the Neuralworks software package (Scientific Computers Limited, UK). This is the industry standard package for neural network simulations and incorporates a variety of different network architectures. For most experiments, 200 input vectors were used for training while the remainder (175) were used as test data. The sensitivity, specificity and accuracy of neural network models were calculated.

Results

Initial experiments using a back propagation network (27 inputs, 5 - 25 hidden units, 1 output) allowed a 60 - 70% correct classification of training data but performed very poorly on test data with never more than 6% accuracy. The problem almost certainly relates to the relatively weak predictive value of most of the risk factors and the number of patients in our database. We tried a number of different neural network architectures from the Neuralworks package. Overall, the best results were obtained from the Boltzmann perceptron network - although, again, no better than 60% prediction could be obtained with test data.

In further experiments, an expert opinion was incorporated along with the clinical data from the above Table in order to increase the number of input vectors in the training set. Thus, each patient data set was rated on a scale of 1 - 10 according to the perceived risk of osteoporosis. Input vectors with a score of 1 were represented once in the raining set, those with a score of two represented two times etc. This yielded a set of 1473 input vectors for training. Results of neural network training with this strategy were encouraging. For example, using a back propagation network (35 inputs, 10 - 30 hidden units and 1 or 3 output nodes), the network converged to a very low RMS error (less than 0.05). This suggested that the data was well represented on the network. The training times for these experiments were considerable - usually of the order of 30,000 epochs (presentations of the data). The optimal performance

was obtained with 28 hidden units in a network which used the delta rule for training and a sigmoid transfer function. We did not find that varying the momentum term or learning coefficient ratio had a marked difference on training or performance. In these experiments, we obtained accuracy in excess of 85% in predicting low bone mineral density in the training set. There was, once more, a considerable decrease in performance on the tests set with only approximately 60% accuracy. There was an improvement in performance when separate networks were used to predict low and high bone mineral density. Combining the output from these networks increased the predictive power on unseen data to about 65%.

Conclusions

These experiments confirm that it is difficult to combine the risk factor and lifestyle data from patients at risk of osteoporosis in a way which allows an accurate prediction of bone mineral density. It does appear, however, that the data can be represented using neural networks although the predictive power on unseen data is relatively low. It should be noted that, in this clinical domain, the predictive accuracy of a method does not have to be perfect since we are merely trying to decide which patients should or should not have measurements of their bone mineral density. A useful instrument would have a high sensitivity but need not be perfectly specific. We are currently examining ways of improving the training of neural networks with clinical data using our chest pain databases. The above results suggest that we may be able to obtain a predictive instrument for osteoporosis risk although, at present, it is not possible to combine the data in a way that would be useful clinically.