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Artificial Neural Network: A Tool for Diagnosing Osteoporosis

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Abstract

The most important concern in the medical domain is to consider the interpretation of data and perform accurate diagnosis. To improve diagnostic process and avoid misdiagnosis, many e-Health systems use artificial intelligence method and especially artificial neural network to manipulate diverse type of clinical data. A common bone disease 'osteoporosis' does not only depend on bone mineral density but also some other factors have significance i.e. age, weight, height, life-style etc. these all factors play considerable role to diagnosis osteoporosis. In this study, we propose a decision making system using the factors other then bone mineral density to provide a convenient, accurate and inexpensive solution to predict future fracture risk.

Keywords: e-Health system, fracture risk, osteoporosis, neural network.

Introduction

Osteoporosis[1] not only depends on bone mineral density (BMD) but also on strength and characteristics of trabecular network[2, 3]. The formation of bone and characteristics of trabeculae depends on many factors that might be the cause of osteoporosis. These causes have significant impact on decision making of osteoporosis and fracture risk. To diagnose any medical related problem accurately, the diagnosis system has to take decisions based on multiple inputs. Achieving the goal of accurate diagnosing, the system engineers have to find the appropriate data, characteristics extraction and analysis of related medical problems.

Due to the heterogeneous and complexity of medical data, the analysis and classification need the AI based technique to manipulate this data i.e. Artificial Neural Network (ANN). Recent studies showed that, majority of researches focus on classification and diagnosing in ANN. Use of ANN for predicting osteoporosis will reduce the diagnosing time and improve the efficiency and accuracy, as ANN showed it in different domain.

Osteoporosis and Fracture Risk: The World Health Organization (WHO) defines the criteria, shown in table-1 and established the definition of osteoporosis based on BMD as "faulty and weakened bone structure due to low amount of bone minerals per unit volume"[4], before this definition the osteoporosis diagnosed after fragility fracture. The bone fragility increases due to the reduction of bone mass and minor force can cause fracture. Still the DEXA scan is a 'gold standard' to diagnosing osteoporosis from BMD.

There are many significant risk factors for osteoporosis; the table-2 shows some of the factors that cause the osteoporosis in all over the world[5]. These factors used in different studies for diagnosing the fracture risk discuss latter.

Table-1
T-score reference values defined by WHO

Diagnosis	T-score Relative to Bone Mineral Density
Normal	BMD value with in 1 SD, (T-score -1)
Osteopenia	BMD value more then 1 SD below the mean and less then 2 SD below the mean, (-1 > T-score > -2.5)
Osteoporosis	BMD value 2.5 SD or more below the mean, (T-score ≤ -2.5)
Severe Osteoporosis	BMD value 2.5 SD or more below the mean with fragility fracture, (T-score ≤ -2.5)

Table-2
Risk Factors for Osteoporosis

General Factors	Family history of osteoporosis, Personal history of fragility fracture as an adult, Postmenopausal, Age 65 and above
Lifestyle Factors	Smoking, Obesity, Alcohol intake more then 2 units per day, Inadequate physical activity, Eating disorders
Nutritional Factors	Excess caffeine intake, Low calcium intake, Vitamin D deficiency, Low body weight (<127 pounds)
Medical Conditions	Weight loss surgery, Bone marrow transplantation, Female athlete triad, Hemophilia, Mastocytosis, Spinal cord transsection, Stroke, Thalassemia, Dialysis
Medications	Long-term glucocorticoid and heparin use, Anti-seizure medication, Aromatase therapy for breast cancer, Aluminum, Cytotoxic drugs, Proton pump inhibitors, Tamoxifen (premenopausal)

Material and Methods

Since 1943 when McCulloch and Pitts proposed a computed neuron[6] worked on fix weights to Donald Hebb[7] that took variable adjusting connection weight, which is the fundamental learning rule in neural networks. Where as, Rosenblatt first proposed the adjustable weighted perceptron model, which used perceptron learning law[8]. The McCulloch defined the simple computational model that takes ‘n’ input and sum it, if the result is above a threshold then output is ‘1’ else ‘0’, as shown in figure-1, the system had lack of learning that latter was included by Rosenblatt.

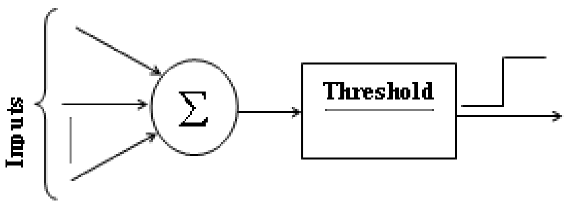

Figure-1
McCulloch-Pitts Neuron

ANN is like a directed graph with weights, the different artificial neurons are (nodes and edges) connected to the input and output. Generally, ANN can be categories into two groups; Feed-forward networks, have unidirectional edges with no loops, and Feed-back networks, have unidirectional edges with loops for feedback connections.

The multilayer perceptron networks are the most commonly used network, composed of nonlinear unidirectional units. It belongs to feed-forward network family. Generally it is static and produce limited output values rather then a sequence. The main concern of any ANN is to estimate the appropriate weight of each input, although out put is well defined.

The learning is also a basic trait of ANN, although the ANN is worked as efficient updating network that perform a specific task and learn connection weights from training data. The efficiency and accuracy are improved in training period by updating input weights. ANN is able to learn automatically during and after training. There are three learning paradigms exist; i. Supervised learning: In this, network has correct answer and weights to be determined to produce the desired result. ii. Unsupervised learning: In this, network correlate the patterns in data and categorize the data according to patterns. iii. Hybrid learning: In this, some of weights assign (supervised) and the remaining weights are determined through unsupervised technique.

To determine the weights, delta learning rule is appropriate that work under supervised paradigm. According to rule, “the change of weight is based on the error between the desired and the actual output values for a given input”. The corresponding learning equation of delta rule is given by,

$$w_{ij}(t) = \eta(b_i - s_i)s_i a_j$$

Where, $s_i = f_i(x_i)$, $x_i = \sum_{j=1}^{M} w_{ij} a_j$, b_i = Desired output from i[th] output unit, a_j = j[th] component of input pattern to j[th] input unit, η = Small positive learning constant.

ANN is used to develop any decision making system in various fields of science and technology i.e. in chemical kinetics[9], agricultural products classification[10], for determination of different species[11], medical image processing[12], recognition of handwritten characters[13] and signature recognition[14].

In the field of medical ANN plays the vital role for diagnosis different diseases. In the study done by Atkov et al.[15] to diagnose of coronary artery disease, he used the clinical data i.e. age, cholesterol level, arterial hypertension as input for ANN system. Ho et al.[16] also used the clinical and demographic data to predict the hepatocellular carcinoma. There are lot of ANN applications developed for cardiovascular diseases, have the accuracy of 90% to 99.2%[15, 17-19], cancer i.e. rectal cancer[20], Tate et al.[21] use attributes of MR in ANN to classify the brain tumors. Brougham et al.[22] used the same concept of Tate and developed the application for lung carcinoma. Yamashita et al.[23] is used 2 clinical and 13 MR found parameters as input in ANN application for diagnosis of intra-axial cerebral tumors. Prediction of discharge in hydraulic system[24] and optimize the treatment process of water[25] both work were also efficiently done by using the artificial neural network.

The major work done in medical domain related to bone are; detecting bone tumor using ANN from MR images[26], reducing unnecessary bone scans by using ANN[27], and prediction of bone damages and injuries obtain by radiographics images using fuzzy logic and ANN classification methods[28]. These three are the major achievement of ANN application in the medical domain related to bone. Jensen et al.[29] used the DEXA values as input in ANN and predict fracture risk, the accuracy of this system is 86.6%. In 1999, Sarah et al.[30] used multiversion system, which predicted the T-Score, by using 20 risk factors and diagnose osteoporosis. This system developed and trained on the data of 274 women. Shaikh et al.[31] presented an alternate approach for diagnosing osteoporosis by investigating the plain radiograph.

Results and Discussion

The multilayer perceptron network is the most often used in the medical diagnosis systems. We also proposed same network for predicting the future fracture risk. The attributes taken for diagnoses are; Age (months), Sex (male/female), Height (inch), weight (kg), Years since menopause (months), Heredity (Y/N), Cigarettes (per day), Alcohol (unit/day), Weight bearing exercise (Y/N), Calcium in diet (mg/day), Low back pain (Y/N), Fracture (Y/N), Height loss (cm), Inactivity (Y/N), and Glucocorticoid (Y/N). These factors have significant impact on bone mass and trabecular microarchitecture. The proposed system does not need of BMD, as calculating BMD from DEXA is an expensive scan and in 3rd world countries common people can not afford this scan. Many osteoporosis and fracture risk predicting tools like Osteoporosis risk estimation score for men[32], Osteoporosis Self-assessment Screening Tool (OST)[33,34], Osteoporosis Index of Risk (OSIRIS)[35] do not required BMD and Fracture Risk Assessment Tool (FRAX)[36,37] uses BMD as optional input. The above studies showed that fracture risk can be assess with out BMD. So, the listed attributes efficiently diagnose the fracture risk. The basic structure of ANN for diagnosis osteoporosis can be seen in figure-2.

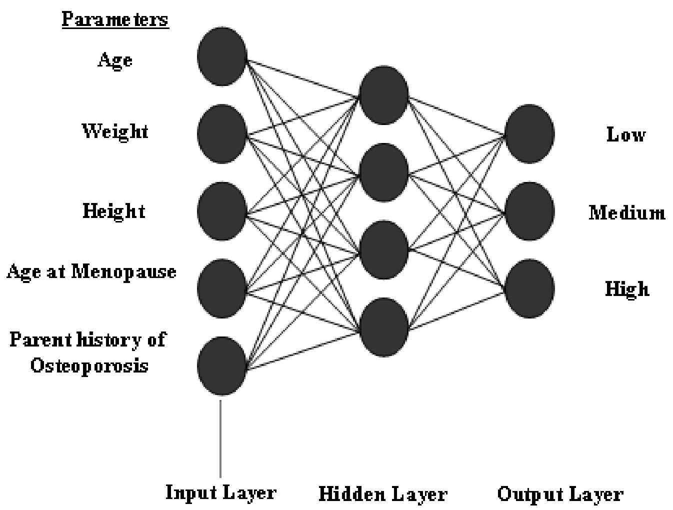

Figure-2
Basic Structure of ANN diagnosis of Osteoporosis

Normally, multilayer perceptron uses backpropogation learning algorithm. These algorithms minimize the error between desired value and output value by using recursively delta rule. Backpropogation calculate error, compute delta (difference), propagate error backwards and then update the weights. After updating, these weights feed in training patterns. Figure-3 shows the major steps to be followed for building ANN for predicting fracture risk.

In the first step we obtained the necessary input information from patients as defined earlier and developed a history of each patient. The attributes or features are then preprocessed and missing data be catered for by inserting zeros in the relevant field, the creation of some additional parameters to indicate population and sample. This process builds the database for training purpose. In the third step, we have to select an appropriate ANN type and architecture, training algorithm and verification method. This is the most important step, the training will need to take place as part of a looped training and validation process. In this process, a core set of parameters is used for the initial training, and then the testing data set is used to evaluate its performance. Errors are then mapped back to absent inputs, and the set re-trained with the additional input. This process is to be repeated until a minimum error is obtained, where the importance and weighting of each input parameter is assessed. In the final step, the system should be tested for new patient. Patient will be examined carefully and if diagnosis correct then the data of patient be included in database.

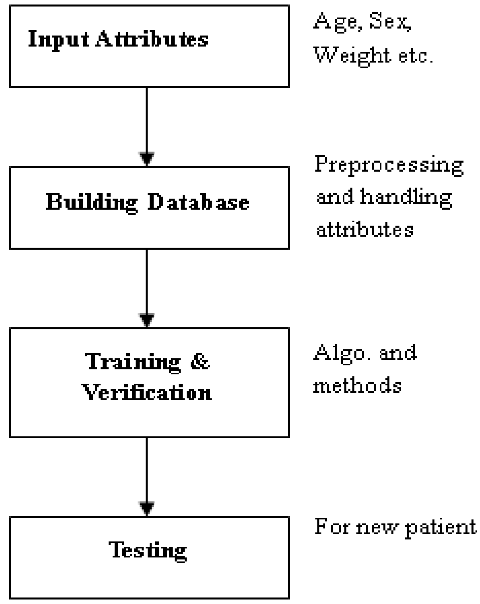

Figure-3
Proposed method for implementing ANN for diagnosis of Osteoporosis

Conclusion

The aim of this study is to evaluate ANN in bone disease ‘osteoporosis’. Prediction of fracture risk and diagnosis of osteoporosis are the major concern of this era. The efficiency, reliability and accuracy of ANN system in different domains have been discussed. The multilayer perceptron with supervised learning algorithm is proposed, to develop the system for diagnosis future fracture risk. The proposed system will provide an invaluable second opinion and an easy investigating tool to facilitate clinicians.

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