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An Improved and Optimal Prediction of Bone Disease Based On Risk Factors

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Abstract: **Bone disease prediction is the most required task in the real world environment which needs to process well to attain the improved prediction of bone diseases. For analysing the bone disease related data sets, various data mining approaches needs to process to obtain the improved prediction of the disease. One of the main data mining approaches which is used for predicting the risk factor of bone diseases are machine learning algorithm. Machine learning is a subfield of computer science that evolved from the study of pattern recognition and computational learning theory in artificial intelligence. Machine learning explores the study and construction of algorithms that can learn from and make predictions on data. The main disadvantage of existing method is that, it will not produce accurate result of bone loss rate due to limited number of features. This drawback is solved in our proposed method by using the relevance based feature selection which tries to predict the result with less availability of feature. Risk factors are fine-tuned using Deep belief network. In this algorithm 2 phases of process are passed out. It includes Pre-training and fine tuning. In the pre-training phase, most important risk factors with model parameters are used to calculate contrastive divergence and it minimizes the record size. In the fine tuning phase comparison is made with the results achieved in the previous phase with the ground truth value g1 and again the same comparison done with ground truth value g2, were g1 is refer to as osteoporosis and g2 is refer to as a bone loss rate. The final results are applied to confusion matrix to describe the performance of classification model based on the comparison results to calculate Accuracy. The experimental result of this work proves that the proposed methodology of this work provides performance improvement than the existing methodology in terms of more accuracy.**

Keywords**: Big data, Data mining, Healthcare**.

I INTRODUCTION

In Bone disease any of the diseases or injuries that affect human bones. Diseases and injuries of bones are major causes of abnormalities of the human skeletal system. Although physical injury, causing fracture, dominates over disease, fracture is but one of several common causes of bone disease, and disease is in fact a common cause of fracture. Bone diseases and injuries were formerly regarded as conditions that were more mechanical than metabolic. An improved understanding of the dual mechanical and chemical function of bone, however, has permitted a more integrated biological view. Osteoporosis is a condition that weakens bones, making them fragile and more likely to break. It's a fairly common condition that affects around three million people in the UK. More than 300,000 people receive hospital treatment for fragility fractures (fractures that occur from standing height or less) every year as a result of osteoporosis. Wrist fractures, hip fractures and fractures of the vertebrae (bones in the spine) are the most common type of breaks that affect people with osteoporosis. However, they can also occur in other bones, such as in the arm, ribs or pelvis. There are usually no warnings you've developed osteoporosis and it's often only diagnosed when a bone is fractured after even minor falls.

A. Motivation of the research

Health care department's plays most important role in the real world environment which needs to be concerned more for treating the patients in time. One of the main diseases which play a greatest role in health care department is the bone disease prediction. Bone diseases cannot be identified in the easiest manner because of numerous number of risk factors. There are various researches has been conducted in the real.

B. Research Objective

The main objective of this thesis is to predict the risk natures present in the human body by analysing the electronic health records based on the different nature of features available online. This is done based on the relevancies present between the different features that are available online. This work attempts to predict the bone related diseases that are present in the system in terms of various risk factors such bone loss rate, osteoporosis risk feature sets and so on. Improved detection of the bone related disease prediction by adapting the learning mechanism in terms of relevancy factor using Deep Belief Network (DBN) to predict bone loss rate.

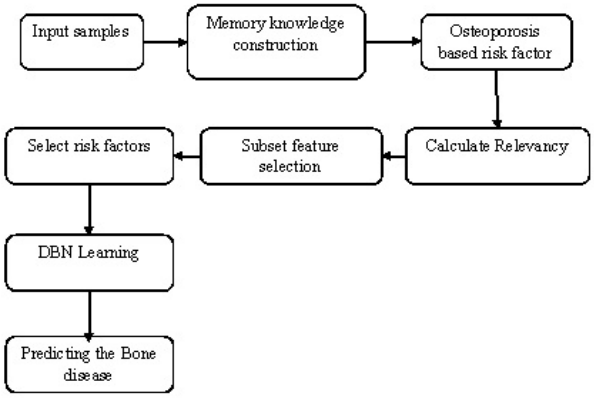
C. Problem definition

The main problem that resides in the real world environment is the bone disease prediction which may cause the serious issues in the human's body. Bone disease prediction would be more difficult process in the real world environment where there are various parameters which cause the diseases. This should be analysed and predicted in the clear way for the clear identification of the bone diseases. The prediction of bone diseases by using the electronic health records available online becomes most complex process which needs to be established well to prevent the serious risk natures. The numerous number of risk factors might poses the complexity of detection of risk factors which is focused in this work.

D. Problem Solution

The issues mentioned above are resolved in this work by introducing the relevance based feature selection approach and the Deep Belief Network based classification approach which is used to predict the bone diseases in terms of various risk factors. The relevance based feature selection is used to select the more relevance features that are present in the bone disease risk factors. The DBN approach is used to accurately classify the risk level of the bone disease risk factors so that prediction accuracy can be improved considerably.

E. Framework of Proposed System



II METHODOLOGY

A. Existing System

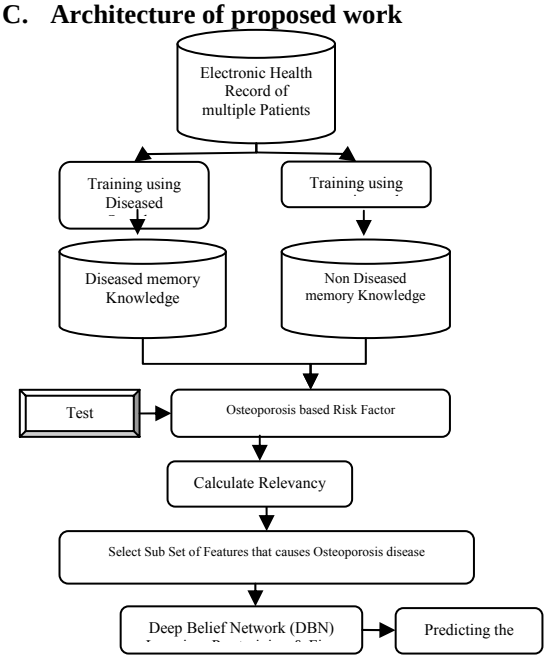
In existing work, it proposes a novel approach for the study of bone diseases in two aspects: bone disease prediction and disease RF selection according to the significance. For clear understanding, we define disease memory (DM) as a model trained by a specific group of samples aiming to memorize the underlying characteristics for this group. In addition, all samples are applied in our model and train a general model which captures the characteristics for both diseased patients and non-diseased patients to predict an unknown sample, denoted by the comprehensive disease memory (CDM) model. Our model is separately trained using diseased samples and non-diseased samples to distinguish their different properties. Bone disease memory (BDM) is a type of DM model which is trained by diseased samples and so it only memorizes the characteristics of those patients who suffer from bone diseases. Similarly, the non-disease memory (NDM) is a model which is trained by the non-diseased samples and memorizes their attributes. Individual training is done on them in order to find informative Risk Factors (RFs) which can be used to distinguish the diseased individuals from non-diseased ones. In other words, different DM models increase the flexibility for exploring different tasks. DM serves as an important embedded module in our framework that has the following nice properties. First, diseased patients and healthy patients are modelled together to establish a CDM which captures the salience of all risk factors by a limited number of integrated features for predicting bone diseases. Second, diseased patients and healthy patients are modelled separately based on their unique characteristics to find the RFs that cause the disease. Third, the model is robust in the presence of missing and noisy data. Last but not least, the model does not require all samples that are considered; instead, it can be trained in a partially controlled manner.

B. Proposed System

Traditionally, Factors selection research has focused on searching for relevant features. Strong relevance of a feature indicates that the feature is always necessary for an optimal subset; it cannot be removed without affecting the original conditional class distribution. Weak relevance suggests that the feature is not always necessary but may become necessary for an optimal subset at certain conditions. Irrelevance indicates that the feature is not necessary at all. An optimal subset should include all strongly relevant features, none of irrelevant features, and a subset of weakly relevant features. However, it is not given in the definitions which of weakly relevant features should be selected and which of them removed.

The major objective of a new framework is to efficiently find the optimal subset. This can be achieved through a new framework, shown in Figure 1 is composed of two steps: First, relevance analysis that determines the subset of relevant features by removing irrelevant ones, and second, Deep Belief Network (DBN) learning is used. In this learning process, 2 stages of process are carried out. They include pre-training and fine tuning. In the pre-training phase, most important risk factors with model parameters are used to calculate contrastive divergence and it minimizes the record size. In the fine tuning phase, comparison is made with the results achieved in the previous phase with the ground truth value g1 and again we compare that result with ground truth value g2, where g1 is referred to as osteoporosis and g2 is referred to as the bone loss rate. The Final results are applied to the confusion matrix to describe the performance of classification model. Based on the comparison results, the following are calculated; Accuracy, Precision, Recall and F-Measure.

C. Architecture of proposed work



D. **Relevancy based feature selection algorithm**

Input: S(F1,F2, ...,FN,C) // a training data set
δ // a predefined threshold
Output: Sbest // a selected subset
1 begin
2 for i = 1 to N do begin
3 calculate $SU_{i,c}$ for F_i;
4 if ($SU_{i,c} > \delta$)
5 append F_i to S'_{list} ;
6 end;
7 order S'_{list} in descending $SU_{i,c}$ value;
8 Fj = getFirstElement(S'_{list});
9 do begin
10 Fi = getNextElement(S'_{list} ,Fj);
11 if (Fi <> NULL)
12 do begin
13 if ($SU_{i,j} >= SU_{i,c}$)
14 remove Fi from S'_{list} ;
15 Fi = getNextElement(S'_{list} ,Fi);
16 end until (Fi == NULL);
17 Fj = getNextElement(S'_{list} ,Fj);
18 end until (Fj == NULL);
19 Sbest = S'_{list} ;
20 end;

For a data set S with N features and class C, the algorithm finds a set of predominant features Sbest. In the first step (lines 2-7), it calculates the SU value for each feature, selects relevant features into S'_{list} based on a predefined threshold d, and orders them in a descending order according to their SU values. In the second step (lines 8-18), it further processes the ordered list S'_{list} to select predominant features. A feature F_j that has already been determined to be a predominant feature can always be used to filter out other features. The iteration starts from the first element in S'_{list} (line 8) and continues as follows. For all the remaining features (from the one right next to F_j to the last one in S'_{list}), if F_j happens to form an approximate value for F_i (line 13), F_i will be removed from S'_{list} . After one round of filtering features based on F_j, the algorithm will take the remaining feature right next to F_j as the new reference (line 17) to repeat the filtering process. The algorithm stops until no more predominant features can be selected.

E. DBN Based Classification Algorithm

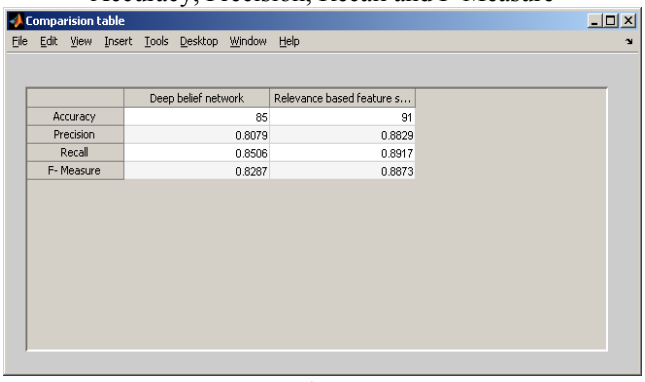
Input: All risk factors, learning rate ϵ, Gibbs round z;
Output: Model parameters M (W; a, b);
Pre-training Stage:
1: Randomly initialize all W; a; b;
2: for t from layer V to h_{l-1} do
3: clamp t and run CDz to update Mt and t+1
4: end for
Fine-tuning Stage:
5: randomly dropout 30% hidden units for each layer
6: loop
7: for each predicted result (r) do
8: calculate cost (c) between r and ground truth g1
9: calculate partial gradient of c with respect to M
10: updateM
11: calculate cost (c') on holdout set
12: if c' is larger than c'_{-1} for 5 rounds then

As shown in DBN Algorithm, the training procedure for DM concentrates on two specific prediction tasks (osteoporosis and bone loss rate) with all Risk Factors(RFs) as the input and model parameters as the output. It includes a pre-training stage and a fine-tuning stage. The first stage is the unsupervised pre-training stage. Here applying the layer-wise Contrastive Divergence (CD) learning procedure for putting the parameter values in the appropriate range for further supervised training. So the result of the pre-training procedure establishes an initialization point of the fine tuning procedure inside a region of parameter space in which the parameters are henceforth restricted. In the second stage, the fine-tuning stage, it takes the advantage of information to train our model in a supervised fashion. In this way, the prediction errors for both prediction tasks will be minimized. Specifically, the parameters from the pre-training stage to calculate the prediction results for each sample and then back propagate the errors between the predicted result and the ground truth (g1) about osteoporosis from top to bottom to update model parameters to a better state. The another type of information, then repeat the fine-tuning stage by calculating errors between the predicted result and another ground truth (g2) about bone loss rate. After the two-stage training procedure, our Diseased Memory DM is well trained and can be used to predict osteoporosis and bone loss rate.

III IMPLEMENTATION

The experimental tests were conducted in the MATLAB simulation environment between the existing and the proposed methodology in terms of performance measures called the accuracy, precision, recall and the F-measure values. It is done to prove the effectiveness of the proposed approach than the existing approach.

Figure 1 Comparison of Existing and proposed Method for Accuracy, Precision, Recall and F-Measure



A. Accuracy Comparison

The accuracy is defined as the correction prediction of the bone diseases with reduced misclassification rate. The accuracy of the proposed method called relevance based feature selection should be more than the existing method called the deep belief network. Accuracy is evaluated as,

$$\text{Accuracy} = \frac{(\text{True positive} + \text{True negative})}{(\text{True positive} + \text{True negative} + \text{False positive} + \text{False negative})}$$

The Accuracy comparison is depicted as graphical notation in the following figure 2

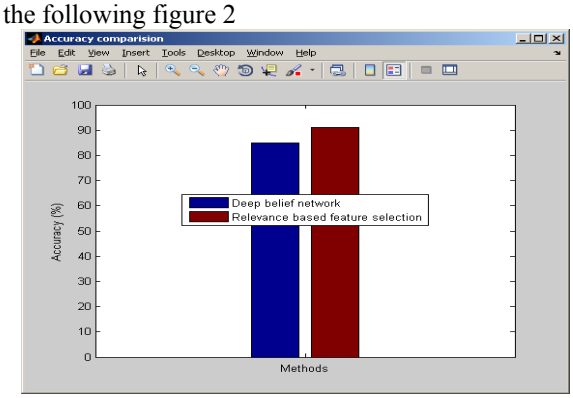


Figure 2 Accuracy comparison of Existing method and proposed Relevance based feature Selection with DBN

In the above graph, proposed and existing research methodologies are compared and evaluated for the performance evaluation. In the x axis methodologies are depicted and in the y axis accuracy in % is depicted. This comparison graph proves that the proposed approach leads to the high accuracy rate of correct prediction of bone disease than the existing approach.

IV CONCLUSION

Healthcare industry is facing challenges now, and recent development in advanced technologies has broad opportunities for confronting such challenges. In this paper risk factor analysis is the process of finding bone diseases in various stages. In the proposed methodology risk factors are analysed in 2 levels. In first level disease prediction is done with relevancies present in different risk factors and the next level is DBN Algorithm is applied on 2 specific prediction tasks. They are osteoporosis and bone loss rate. All risk factors as the input and model parameters as the output the experimental result of this work proves that proposed methodology of this work provides performance improvement then the existing methodology in terms of more accuracy.

V FUTURE WORK

In future following research scenarios can be considered for the efficient prediction of bone related diseases. Different machine learning algorithms can be used to label the features of bone diseases accurately. The various prediction methodologies can be incorporated to predict the bone disease accurately. Additional risk feature sets can be incorporated with the available features to improve the detection accuracy. The relevancy based feature selection with DBN learning approach is used to improve the detection accuracy

REFERENCE

[1] Karamjit Kaur and Rinkle Rani, "Managing Data in Healthcare Information Systems: Many Models, One Solution", Published by IEEE computer society 2015, pp. 52-59.

[2] Hui Li, Xiaoyi Li, Murali Ramanathan, and Aidong Zhang, "Prediction and Informative Risk Factor Selection of Bone Diseases", Published by IEEE/ACM Transactions On Computational Biology and Bioinformatics, Vol. 12, No. 1, January/February 2015, PP. 79-91.

[3] Uma Srinivasan, *Capital Markets Cooperative Research Centre, Australia* "Anomalies Detection in Healthcare Services", Published by the IEEE Computer Society IT Pro November/December 2014, pp. 12-15.

[4] Daniel R. Harris, Darren W. Henderson, Ramakanth Kavuluru, Arnold J. Stromberg, and Todd R. Johnson "Using Common Table Expressions to Build a Scalable Boolean Query Generator for Clinical Data Warehouses" Published by IEEE Journal of Biomedical and Health Informatics, Vol. 18, no. 5, September 2014. Pp.1607-1613.

[5] Shancang Li, LiDaXu and XinhengWang "A continuous biomedical signal acquisition system based on compressed sensing in body sensor networks" Published by IEEE Transactions on Industrial Informatics, Vol. 9, No. 3, August 2013.PP 1764- 1771.

[6] Carlos Ordonez, "Comparing Association Rules and Decision Trees for Disease Prediction", Proceedings of the international workshop on Healthcare information and knowledge management, Pages 17-24, 2006

[7] World Health Organization, "WHO scientific group on the assessment of osteoporosis at primary health care level," Brussels, Belgium, Summary Meeting Rep., May 2004. Web link: http://www.who.int/chp/topics/Osteoporosis.pdf

[8] B. J. Riis, "The role of bone loss," Amer. J. Med., vol. 98, no. 2, pp. 29S–32S, 1995. Web:http://www.ncbi.nlm.nih.gov/pubmed/7709930.

[9] G.Lemineur,R.Harba,N.Kilic,O.Ucan,O.Osman, and L. Benhamou, "Efficient estimation of osteoporosis using artificial neural networks," in Proc. IEEE 33rd Annu. Conf. Ind. Electron. Soc., 2007, pp. 3039–3044.

[10] Hui Li, Xiaoyi Li, Lawrence Bone, Cathy Buyea, Murali Ramanathan, Aidong Zhang, "3D Bone Microarchitecture Modeling and Fracture Risk Prediction", Proceedings of the ACM Conference on Bioinformatics, Computational Biology and Biomedicine, Pages 361-368, 2012

[11] Dumitru Erhan, Aaron Courville, and Yoshua Bengio, "Understanding Representations Learned in Deep Architectures", http://memkite.com/deep-learning-bibliography/

[12] Yichuan Tang and Chris Eliasmith,"Deep networks for robust visual recognition", Proceedings of the 27th International Conference on Machine Learning (ICML-10), Year: 2010,Pages: 1055-1062

[13] Yichuan Tang, Ruslan Salakhutdinov, Geoffrey Hinton, "Robust Boltzmann Machines for Recognition and Denoising", Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on 16-21 June 2012

[14] Nicolas Le Roux and Yoshua Bengio, "Representational Power of Restricted Boltzmann Machines and Deep Belief Networks", Neural Computation, Volume 20 Issue 6, June 2008, Pages 1631-1649

[15] D. Black,M. Steinbuch, L. Palermo, P. Dargent-Molina, R. Lindsay, M. Hoseyni, and O. Johnell, "An assessment tool for predicting fracture risk in postmenopausal women," Osteoporosis. Int., vol. 12, no. 7, pp. 519–528, 2001.