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Assessment of Bayesian Estimators for Osteoporosis Analysis

ORIGINAL

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Abstract

Background: Bayesian classifiers have the advantage of determining the class to which a given record belongs compared to traditional classifiers, taking as base the probability of an element belonging to a class. Thus, the diagnosis of diseases such as osteoporosis and osteopenia can become faster and precise. This paper presents an assessment of the accuracy of the Bayesian classifiers Bayes Net, Naive Bayes and Averaged One-Dependence Estimators to support diagnoses of osteopenia and osteoporosis.

Method: The methodology that guided the development of this research relied on the choice of database, the study of the Bayes Net, Naive Bayes and Averaged One-Dependence Estimators algorithms, and the description of the experiments.

Results: The algorithm with the highest specificity was Bayes Net, (53.0±0.27). The highest accuracy was obtained using the AODE classifier (83.0±0.17). Our results showed higher mean instances correctly classified using the Naive Bayes algorithm (82.84±14.42), and the average of incorrectly classified instances was higher for Bayes Net (17.46±14.76).

Conclusion: Based on the statistical measures analyzed in the experiments (instances classified correctly and incorrectly, the kappa coefficient, mean absolute error, sensitivity, specificity, accuracy, recall, F-measure, and Area Under Curve (AUC)), all classifiers showed good results, thus, given these data, it is possible to produce a reasonably accurate estimate of the diagnosis.

Keywords
Medical Informatics; Artificial Intelligence; Data Mining; Bayes Theorem; Osteoporosis.

Introduction

Osteoporosis is a disease that results in the decline in the health of the world population and challenges the public health and medical professions. It is important to focus on this disease due to the morbidity and mortality resulting from osteoporotic fractures, yet the majority of patients suffering from this condition remain untreated: less than 20% of individuals with fragile bone fractures receive adequate therapy [1].

Osteoporosis is characterized by low bone density and microarchitectural deterioration of bone tissue, leading to increased skeletal fragility and increased risk of fractures, particularly in the backbone, hip, forearm, and humerus [2]. Although the risk of fractures increases due to decreased bone density, most fractures occur in patients with osteopenia because the majority of the population is classified as having this disease [3]. Osteopenia is a skeletal disorder defined according to the criteria of the World Health Organization (WHO) by a decreased bone mineral density t-score between -1 and -2.54 for either the spine or hip [4].

The incidence of osteoporosis is increasing due to the aging population, ranging from 14% to 29% in women over 50 years of age and affecting up to 70% of women over 80 years old. However, in Brazil, there are no studies that definitively determine the incidence of the disease because the racial integration and heterogeneity of the regions suggest different risk factors [2].

This disease is a major cause of morbidity and mortality in the elderly. Although less common in men than in women, more than 8 million men in the United States have osteoporosis [5], and the mortality rate for hip fractures (as well as other vertebral fractures) is higher in males.

Data mining (DM) offers methods and tools based on statistical concepts and artificial intelligence machines capable of assisting in the construction of more significant knowledge. DM is an automated discovery process to find relevant and implicit information in large databases. DM techniques attempt to discover patterns and useful rules that are otherwise small or imperceptible and can aid the researcher in their evaluation [6], thus allowing differentiated analyses of the data, the development of predictive models and the formulation of hypotheses.

The tasks related to DM include a classification system to establish a function that maps a set of elements to a number of classes. In recent years, this system has been the most utilized tool in health care [7]. Therefore, to address the uncertainty inherent in biomedical diagnoses, Bayesian classifiers, which are based on statistical models, have the advantage of determining the class to which a given record belongs compared to traditional classifiers, taking as base the probability of an element belonging to a class. Thus, the diagnosis of diseases such as osteoporosis and osteopenia can become faster and precise [8].

This paper presents an evaluation of the accuracy of the Bayesian classifiers Bayes net (BN), Naive Bayes (NB) and Averaged One-Dependence Estimators (AODE) to support the diagnosis of osteopenia and osteoporosis.

Methods

Detailed below is the methodology that guided the development of this research, including the choice of the experiments.

The database used in the experiments originated from a transverse study wih a consecutive sample involving 1871 women in southern Santa Catarina who were subjected to bone densitometry measurements under a specialized service from 2010 to 2012. This study was approved by the Ethics Committee under protocol 82939/2012. The data collected contain census characteristics because the subjects represented all of the different ethnic groups within the general population. The service consulted provides patient care through the Brazilian Unified Health System and private plans.

The variables used in the experiments are presented in **Table 1**.

Table 1. Variables used in the experiments.

Description	Attributes – preprocessed database
Dichotomous Fracture	1-Yes, 2-No
Femur Dichotomous	1-Yes, 2-No
Dichotomous Column	1-Yes, 2-No
Forearm Dichotomous	1-Yes, 2-No
Costa Dichotomous	1-Yes, 2-No
Menopause Dichotomous	1-Yes, 2-No
Calcium Dichotomous	1-Yes, 2-No
TRH Dichotomous	1-Yes, 2-No
Oophorectomy Dichotomous	1-Yes, 2-No
Rape of vulnerable	1.64 (1.10–2.45)
Hysterectomy Dichotomous	1-Yes, 2-No
Dichotomous Average Age	1- 49 or younger, 2- 50
Dichotomized To 25 And IMC	1-25 or younger
25 Or More	2- 26 or older
Thyroid Medication For	1-Yes, 2-No
Dichotomous Outcome	1-normal, 2- osteopenia and osteoporosis

The Bayesian classifiers used in this research are based on the Bayes theorem, which calculates the probability of an instance belonging to a certain pre-determined class. This instance is assigned to the class with the highest probability after applying the Bayes theorem [6].

Bayesian classification has certain advantages over classical classification because the graph structure is fixed, and the values are unconditionally independent on each other such that the classifier used to estimate the parameters implied by the algorithm becomes simple because the dependency ratio is fixed and reduced by two variables –thus, only numerical parameters can be learned [9]. The algorithms used in the tests were Naive Bayes, Averaged One-Dependence Estimators and Bayes Net and are described below.

a) **Naive Bayes:** The NB learns the conditional probability of each data attribute belonging to a particular class from a sample of data. Then, given a new case, this algorithm uses the Bayes rule to calculate the conditional probability of the class to which the element belongs given a set of attributes and select the value of the class with the highest probability a posteriori [10]. It is considered the most efficient classifier because its main features are simplicity and precision, and although its structure is always fixed, some studies have shown high accuracy and low error rates associated with the NB [11].
b) **Averaged One-Dependence Estimators:** This algorithm is considered an improvement on the NB and an interesting alternative to other semi-naive approaches. It provides a good trade-off between efficiency and performance. To maintain efficiency, the AODE is restricted to the exclusive use of one estimator for the dependency relationship. Specifically, the AODE can be considered as an ensemble of SuperParent One-Dependence Estimators (SPODEs) because every attribute depends on the class and another shared attribute, which is designated as the superparent [12].
c) **Bayes Net:** This algorithm belongs to a family of constraint-based algorithms that use conditional independence tests (based on information measures) to decide if a pair of nodes is to be connected or disconnected [13]. The differences of Bayes-Net with respect to its relatives are the use of the Bonferroni correction to adjust the threshold used in every statistical test, the depth of the independence tests (i.e., how many variables are considered in the conditional set), and the inclusion of a parameter to control the significant percentage of information gain [13].

The experiments included the following steps: data cleaning and binarization; transformation of

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variables; selection tool; data mining; variable selection and use of classifiers.

In data cleaning and binarization, records with inconsistent information were either corrected or deleted (if missing information); however, it was found that some of the variables associated with the diagnosis were already binarized (according to medical specialist). In the transformation of variables, fields containing spaces were replaced by underlines and empty fields by question marks.

The Weka shell was chosen for the experiments that pulled data from studies conducted with the Tanagra and Knime tools, as Weka provides better measures than the others for evaluating the knowledge generated.

The original database was developed using the Statistical Package software for Social Sciences (SPSS) (.sav format) and exported to .csv format for preprocessing performed using Excel. After the preprocessing step, the Excel database (.csv) was exported to .arff format (used in the Weka tool) for data mining, which included the use of the Bayesian classifiers Naive Bayes, Bayes Net and AODE.

Results

Approximately 327 experiments were performed and selected for evaluation. The Weka tool was used to evaluate the accuracy, the correct and/or incorrect classification of instances, the kappa coefficient, the mean absolute error, sensitivity, specificity, recall, F-measure, Area Under Curve (AUC) ROC, algorithm execution time and overall accuracy.

Our results showed higher mean instances correctly classified using the Naive Bayes algorithm (82.84±14.42), and the average of incorrectly classified instances was higher for Bayes Net (17.46±14.76). The result for the kappa coefficient, related to the agreement between the result of the classifier and the result presented in the database by the specialist, was higher for the Bayes Net algorithm (0.33±0.29).

The lowest mean absolute error was demonstrated with the AODE algorithm (0.18±0.14), which also showed higher sensitivity (84.0±0.14). However, the algorithm with the highest specificity was Bayes Net, (53.0±0.27). The highest accuracy was obtained using the AODE classifier (83.0±0.17). All evaluation measures considered are presented in **Table 2**.

Discussion

Bayesian classifiers are based on Bayes' theorem and use the fundamentals of conditional probability in the classification task. Thus, they calculate the probability of an instance belonging to each predetermined class, and instance is assigned to the class with the highest probability after application of the theorem [6].

Osteoporosis, osteopenia and osteoporotic fractures generate high health care costs, which has a significant impact on public health, cause high morbidity and mortality of the affected population and vary considerably among different countries, especially due to population differences and available resources for the prevention and treatment of these diseases [14].

Several strategies for the prevention and treatment of pathological fractures are available; however, the optimal approach to classify individuals at high risk who would benefit from improved therapies remains a challenge [15]. In this context, the DM can render this process faster and more accurate, enabling therapeutic treatment at the early stages of bone degradation.

Our study showed good sensitivity measures, specificity and accuracy for the three classifiers analyzed, with AODE showing the highest accuracy (83.0) and sensitivity (84.0), followed by Naive Bayes, which had an accuracy of 82.0 and sensitivity of 83.0.

In this context, a study on neonatal jaundice performed in 2011 by the Department of Obstetrics in

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Table 2. Comparison of measures for evaluation

Description	Algorithm	Average	CI	SD	Minimum	Maximum
Instances classified correctly	Bayes Net	82.54	79.53-85.54	14.76	41.04	99.67
	Naive Bayes	82.84	79.97-85.72	14.42	41.20	99.57
	AODE	84.52	81.69-87.34	14.08	42.81	99.84
Instances classified incorrectly	Bayes Net	17.46	14.45-20.47	14.76	0.32	58.95
	Naive Bayes	17.15	14.27-20.03	14.42	0.43	58.79
	AODE	15.48	12.66-18.30	14.08	0.16	57.19
Kappa	Bayes Net	0.33	0.27-0.40	0.28	0.00	0.95
	Naive Bayes	0.31	0.26-0.37	0.28	0.00	0.96
	AODE	0.34	0.28-0.40	0.29	-0.01	0.97
Medium-absolute error	Bayes Net	0.19	0.16-0.22	0.14	0.00	0.43
	Naive Bayes	0.19	0.16-0.22	0.14	0.01	0.43
	AODE	0.18	0.15-0.21	0.14	0.00	0.43
Sensitivity	Bayes Net	0.82	0.79-0.85	0.15	0.41	0.80
	Naive Bayes	0.83	0.80-0.86	0.14	0.41	0.99
	AODE	0.84	0.82-0.87	0.14	0.43	0.99
Specificity	Bayes Net	0.53	0.48-0.59	0.27	0.00	0.95
	Naive Bayes	0.51	0.46-0.57	0.27	0.00	0.96
	AODE	0.49	0.43-0.55	0.29	0.00	0.95
Accuracy	Bayes Net	0.81	0.78-0.85	0.16	0.38	0.99
	Naive Bayes	0.82	0.78-0.85	0.16	0.37	0.99
	AODE	0.83	0.79-0.86	0.17	0.12	0.99
Recall	Bayes Net	0.82	0.79-0.85	0.15	0.41	0.99
	Naive Bayes	0.83	0.80-0.86	0.14	0.41	0.99
	AODE	0.84	0.82-0.87	0.14	0.42	0.99
Measure-F	Bayes Net	0.81	0.78-0.84	0.16	0.38	0.99
	Naive Bayes	0.81	0.78-0.84	0.16	0.37	0.99
	AODE	0.83	0.80-0.86	0.15	0.39	0.99
AUC	Bayes Net	0.79	0.75-0.82	0.17	0.04	0.99
	Naive Bayes	0.79	0.76-0.89	0.17	0.04	0.99
	AODE	0.81	0.78-0.85	0.16	0.04	0.99
Time	Bayes Net	0.02	0.01-0.02	0.02	0.00	0.12
	Naive Bayes	0.00	0.00-0.00	0.01	0.00	0.04
	AODE	0.00	0.00-0.01	0.01	0.00	0.04

CI: Confidence interval. SD: Standard deviation.

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a hospital in Portugal evaluated the J48 classifiers, simple CART, Naive Bayes, Multilayer Perceptron, Sequential minimal optimization (SMO) and regression logistics [16]. The most accurate algorithm identified was Naive Bayes (88.0).

Similar rates were also achieved in our study regarding the Naive Bayes algorithm. One suggested explanation for the acceptable performance of this classifier is the model's ability to assign the correct class to a test observation provided that the probability of belonging to this class is greater than the probability of belonging to another class or classes, even though the probability estimates may not be accurate [17].

This algorithm was also used in a study conducted at the University of South Carolina (USA) based on the early diagnosis of melanoma [18]. In this study, they considered three classifiers - artificial neural networks, Naive Bayes, and the nearest neighbor algorithm. The Naive Bayes algorithm achieved the highest accuracy, sensitivity and specificity (both 89%) for the outcome considered. The diagnostic accuracy of the algorithm is based on a simple Bayesian classifier, in which all attributes are independent of each other; in other words, no attribute influences any other one [19].

Considering the use of the Bayes Net classifier, a study of breast cancer data, skin diseases and diseases of the spine at the University of Wisconsin (USA) [20], evaluated (in addition to the algorithm mentioned above) the logistic model tree and showed higher accuracy associated with Bayes Net (97.0).

The applicability of Bayesian classifiers such as the Bayes Net algorithm is not restricted only to health but encompasses several areas, as shown in research on the prediction of academic dropout at the University of Rio de Janeiro, suggesting sufficient accuracy in the use of the Bayes Net algorithm (89.0) [21]. Some authors attribute the evaluation measures of this algorithm to the fact that the classifier does not allow interactions between attributes, a characteristic that can provide greater wealth in modeling and understanding of the phenomenon under study [13].

In the case of Bayes Net, the Bayesian network is constructed by either adding or deleting arcs, considering only individual pairs in relation to compliance of the attributes; that is, the rest of the nodes are not considered in analysis [13]. This reason is why the information gain measures used in Bayes Net are referred to as "local"; in other words, the network construction does not depend on a function that evaluates the entire network each time a request for either insertion or removal of nodes or arcs is created. This feature is advantageous when there are a large number of attributes, because global scoring functions cannot minimize error sites associated with the performance of the resulting network classification. Although this algorithm has good efficiency, it is not a good classifier [13].

Furthermore, one advantage of Bayes Net over Naive Bayes is that the former performs a correct subset feature selection and omits variables that are not significant from the analysis. Additionally, Bayes Net does not make the strong assumption made by Naive Bayes that the variables are conditionally independent given the class variable [13].

AODE, which had the highest accuracy in our experiments, was also the most accurate classifier in the classification of genetic sequences [12]. It was used in a support system for clinical decisions regarding the diagnosis of celiac disease in a survey conducted in 2011 by the Department of Pediatrics at the University of São Paulo [22]. In this study, the database consisted of 178 records and was rated by 5 artificial intelligence techniques (decision trees, Bayesian networks, nearest neighbor algorithm, support vector machines and neural networks). Among the algorithms analyzed, AODE showed the greatest accuracy (84.0), a value similar to our findings (83.0). Compared to Naive Bayes, AODE appears to be the best classifier for

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global data sets and to enable improved data characterization [23].

Conclusion

The development of this research includes the understanding that Bayesian classifiers use the Bayes theorem, which allows them to stand out because of their efficiency, speed and accuracy, thus explaining its usefulness in the diagnosis process.

Based on the results of analyzing statistical measures in the experiments described here (instances classified correctly and incorrectly, the kappa coefficient, mean absolute error, sensitivity, specificity, accuracy, recall, F-measure, and AUC), all classifiers showed good results, thus, given these data, it is possible to produce a reasonably accurate estimate of the diagnosis.

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Conflict of Interest

The authors have declared no Conflict of interest.

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