Artificial Intelligence (AI) Techniques Applied for the Development of a Clinical Decision Support System (CDSS) for Diagnosing Ischemic Heart Disease (IHD)

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ABSTRACT

Ischemic Heart Disease (IHD) is difficult to diagnose since most of the symptoms and clinical presentations are similar to other diseases. It is a very common, harmful disease, which is identified mostly during the mortality of an individual. The objective is to build a clinical decision support system, which will diagnose the presence of IHD with an integrated automated classifier using Artificial Intelligence (AI) techniques. A retrospective data set that included 800 clinical cases was taken for the work. A total of 88 sets were discarded during pre-processing. Tests were run on 712 cases using the Weka classifiers available in Weka 3.7.0. Out of 113 classifiers, 16 were identified to be the best based on the following parameters: sensitivity, specificity, accuracy, F-measure, kappa statistic, correctly classified cases, time taken to run the model, and the Receiver Operating Characteristic (ROC) curve. The diagnoses made by the Clinical Decision Support System (CDSS) were compared with those made by physicians during patient consultations. The KSTAR algorithm showed the best diagnoses with the highest accuracy 97.32%, sensitivity 98%, specificity 97% kappa 0.95, and ROC 0.995. The authors thus conclude that a CDSS can be developed to assist expert physicians in separating the positive and the negative cases of heart disease.

General Terms

Artificial Intelligence, Classification

Keywords

Clinical Decision Support System (CDSS); Artificial Intelligence (AI) techniques; Ischemic Heart Disease (IHD); Sensitivity; Specificity; Accuracy; F-measure; Kappa statistic; Receiver Operating Characteristic (ROC).

1. INTRODUCTION

Ischemic Heart Disease (IHD) is difficult to diagnose and very commonly identified only during the mortality of an individual. According to World Health Organisation (WHO) in India 70% of coronary death occurs in subjects less than 70 years of age but in North America and Western Europe same percentage of death occur in subjects older than 70 years. [1]. In India, Coronary Heart Disease (CHD) is an epidemic [1]. Diagnosis criteria in western medicine is referred as "naming and diagnosis criteria of ischemic heart disease" issued by the International Society of Cardiology and the Joint Subject Team on the standardisation of clinical naming in the WHO [3]. Among Indians, CHD has reached the level of epidemic [4]. With increasing number of CHD cases India is facing a major shift in health [5]. The trend released by WHO

Statistics 2012 is a worrying factor for India [6]. Between the years 1960 and 2000 the prevalence of CHD has raised two fold in rural areas and six fold in urban areas among the adults over 20 years of age [7] and compared to general population of United States the pervasiveness of CHD is approximately four times higher in Indians [8]. Compared to the general population in the United States, the prevalence of CHD in Asian Indians is approximately four times higher [8].

According to WHO statistics [7] in India about 24% of men and 22.6% of women aged 25 year and above are suffering from high blood pressure (BP). Over one in ten men and women aged 25 years and above have high blood sugar. More women in India (2.5% of adults aged 20 years and above) are obese compared to Indian men (1.3%). Almost one in five (19%) boys, aged 13-15 years (adolescents), and 8% girls smoke tobacco. Disparities between countries exist because of cardiovascular diseases [9], with respect to Body Mass Index (BMI). These findings support the fact that obesity may be a pointer to eventual heart disease. As compared to other population, Indian population has higher long-term case fatality following acute coronary syndrome [11]. In Indian population the socio-economic gradient is the major CHD risk factor [12][13].

As per the Medical Council of India, the total number of registered allopathic doctors in the country is as little as under 700,000. Out of 1.22 billion 72 population, 72.2% lives in villages and remaining 27.8% lives in towns and urban area [14]. According to this statistic there is only one allopathic doctor for 2000 patients [15]. This work is expected to help in the classification of the risk levels of the heart disease that causes sudden death. Knowing the risk levels, people can take adequate measures to meet the doctor depending on the severity of the disease, or follow strict dietary rules to avoid problems in future.

2. MATERIALS AND METHODS

This study, approved by the Madras Medical College and the SASTRA University (Shanmugha Arts, Science, Technology & Research Academy), was conducted in the Cardio Thoracic Department of the Madras Medical College. The development of a CDSS for diagnosing IHD consisted of four phases: I, II, III, and IV as in Figure 1. In Phase I, the authors developed an attribute set system for IHD. In Phase II, the authors developed, assessed, and implemented a system for acquisition and retrieval of clinical data in the outpatient clinic. Training and testing databases were constructed here. In Phase III, the data is coded. A training database was tested with a set of automated classifiers. In Phase IV, the authors evaluated the developed CDSS. In this paper, the authors have

designed a heart system enquiry diagnosis scale [16], in which the symptoms have been defined clearly, and the detailed collecting methods have been listed. The total dataset is divided into training and testing data. A 10-fold cross validation has been used. The different classifiers of Weka are trained using the training set and then, the sensitivity and the specificity of the classifier (once trained) are evaluated on the test set. This evaluation is repeated ten times, alternating the test set used each time. This method reinforces the validation process, so that the sensitivity and specificity values are the average of the ten validation folds [17]. A training set is a set of data used to discover potentially predictive relationships between the input and output. The training set is used by the Weka classifiers to build a model. This model is used to predict the output for the test attributes.

2.1 Phase I – Attribute construction

The first stage of the work is attribute identification. Various literature and bench-mark UCI datasets [18] have been analysed and discussed with experts. The attributes, which will help in supporting the clinical decision, will be designed as shown in Table 1. These attributes can be easily collected through medical camps in a particular area. The method is feasible under the assumption that people are already familiar with the presence of cholesterol and diabetes. In future, these measures as values may be obtained through instruments available in the market.

2.2 Phase II – Database construction

A retrospective database (DB1) comprising the first-appointment record of 712 clinical cases was created for algorithm training. Confirmed IHD cases accounted for 68% of all records, while the remaining diagnoses had signs, symptoms and complaints that were shared with clinical cases of IHD (non-IHD group; NIHD). Patients in the IHD group were classified according to their ECG results, based on the gold standard [2]. Similarly, a testing database (DB2) was created for classifier evaluation. An experimental model was designed to determine the classifiers that were to be integrated into CDSS under development. Automated classifiers available from the Waikato Environment for Knowledge Analysis (Weka 3.7.0) software [19] were tested. Weka is a comprehensive set of libraries organised in Java packages of different classes that implements machine learning and data mining algorithms [11]. A total of 16 attributes (nominal, numeric) of signs, symptoms, and high-risk groups were listed (Appendix A). All clinical data relating to medical histories were coded and given 'y' (yes) or 'n' (no) values depending on whether the patient had a certain symptom. Certain attributes like height, weight, BMI, systolic and diastolic BP were numeric values. The target variable was the diagnostic variable out, with Risk or No Risk categories.

2.3 Phase III - Training and testing classifiers

AI Techniques

1. Lazy Classifiers: All the training samples are stored till a new sample needs to be classified. This way lazy classifiers are varying from decision tree classifiers, which build a general model before receiving new samples. In the Weka IBk, the authors use the Locally Weighted learning (LWL), KSTAR, and Lazy Bayesian Rules (LBR) classifiers. KSTAR has demonstrated better accuracy for our dataset.

2. Artificial Neural Net (ANN): It is like the human natural neural network with a distributed parallel processor made up of neurons, which are small processing units which have the ability to store knowledge from a database. This knowledge is used for classifying a new data. In this study, the parameters of learning rate (L), varying between 0.3 and 0.5, momentum (M), varying between 0.2 and 0.5, and 500 epochs to training (default), were applied to the algorithm Multilayer Perceptron (MLP).

3. Decision Trees: A sequence of tests on attributes using "if..then..else" is performed for classification of tuples according to class label. Here, the ADTree [19], SimpleCart [11], and J48 algorithms, which are trees of C4.5 type [12] are used.

4. Bayesian Classifiers: By assuming the conditional independence of the attributes in the NaiveBayes, NaiveBayesSimple, and BayesNet algorithms [16], by calculating the probability for each class, the classification was achieved. The algorithms AODE [14] and AODEsr [17] minimised the presupposition of conditional independence, thereby resulting in better precision.

5. Support Vector Machines (SVMs): Classification here was achieved by separating the data according to the variation in the parameters of a support vector. In this study, different kernels (polykernel, radial basis function, sigmoid and linear) were used with different penalty parameters for the error term (C) and kernel parameter (G). The parameters C and G are varied between 1×10^{-10} and 1×10^{10} [23].

6. K-nearest Neighbours: According to the distance, mostly Euclidean distance, classification according to the closest data point is done. The algorithm LBR [20] is a Bayesian classifier in which, lazy learning techniques are applied to induce Bayesian rules. In this study, in the algorithm IBk [21], the number of neighbours (k) varied between 1 and 20. In the algorithm KSTAR [19], the parameter for overall blending (B) varied between 10 and 100. The algorithm (LBR) was tested with the standard parameters.

7. The variability of the algorithms for each technique and the variations in the parameters resulted in 59 models. From these, 16 best models were tabulated in Table 2. In the Data Preprocessing the values were discretised. In Weka 3.7.0, the cross-validation test was undertaken to estimate the accuracy rate of a classifier with the standard parameters and a 10- fold cross-validation for accuracy estimation. It is understood that various techniques showed different accuracies with different datasets. Our dataset had an accuracy of 97.02%.

Algorithm selection

The algorithm with the greatest area under the ROC curve (AUC) was selected. The ROC curve was a graphical plot of sensitivity versus one minus specificity, and was used to evaluate classification and prediction models [19]. In the Weka 3.7.0 software, the AUC is calculated by means of the sensitivity and specificity of each of the folds used in training the classifier. The CDSS was designed such that it would issue a warning when the probability of IHD occurrence went above 50%.

2.4 Phase IV – CDSS evaluation

The CDSS was then evaluated using the testing dataset DB2. The data relating to each clinical case in DB2 were recorded in the CDSS. The probabilities of IHD occurrence were

recorded for comparison against the diagnostic intuition that had been recorded by a medical provider during a consultation.

Statistical analysis

Cross-validation with ten subsets (ten-fold cross-validation) was used for testing. To evaluate and compare algorithms with regard to the accuracy of the classification, the parameters used for selecting the algorithm were the highest values for the AUC, sensitivity, specificity and accuracy rate [22]. A comparative analysis between the AUC results for each algorithm before and after the variable selection was

performed to determine the best parameters for the algorithm to be selected. Kappa statistics were used to evaluate the agreements between the CDSS and the gold standard: between the physician's impressions, i.e. relating to the diagnostic impression recorded by physicians and their tutors during consultations, and the gold standard, and between the CDSS and the physician's impression. In this manner, the diagnostic reliability of the CDSS is assessed.

Figure 1. The four phases of CDSS for IHD classification

Table 1. Attributes identified for heart disease identification

No.	Name	Description
1	Age	Age in years
2	Sex	1 = male ; 0 = female
3	Menopause	0 = No ; 1 = yes
4	Height	≤ 140 cm , 141 cm – 170 cm, ≥ 171 cm
5	Weight	≤ 50 Kg, 51 Kg – 75 Kg, ≥ 76 Kg
6	BMI	Body Mass Index
7	Waistcircum	Measure of circumference of waist
8	SBP	Systolic Blood Pressure
9	DBP	Diastolic Blood Pressure
10	Diabetes	Presence is treated as 1, absence as 0.
11	Chol	Presence of cholesterol is treated as 1, absence as 0.
12	Thy	Presence is thyroid is treated as 1, absence as 0.
13	Per_hab	Personal habits of drinking/smoking is recorded as 1, 0 otherwise.
14	Fam_hist	Family history of heart disease presence is treated as 1 else as 0.
15	Type A	Type A personality is treated as 1, 0 otherwise.
16	Out	Output, No risk as 0, Low risk as 1, Medium risk as 2 and High risk as 3. Later for 2 class problem, No risk as 0 and the Low, Medium and High as 1

Table 2. Best 16 Classifier Models

Classifier Name	Classifier Name
K star	NNge
IBK	Decorate
IB1	ClassificationViaRegression
RandomTree	FT
Id3	NB
RandomCommittee	RotationForest
Rules	LMT
RandomForest	MLP

Table 3. Performance measures of the best 16 Classifier Models

S.No.	Classifier Name	Correctly classified	Incorrectly classified	Sensitivity	Accuracy	Precision
1	KSTAR	97.32%	2.68%	97.80	97.32	97.64
2	IBK	97.22%	2.78%	97.16	97.22	98.14
3	IB1	96.83%	3.17%	97.30	96.83	97.30
4	RandomTree	97.123	2.877	97.15	97.12	97.97
5	Id3	97.22%	2.68%	97.47	97.32	97.97
6	RandomCommittee	97.22%	2.78%	97.16	97.22	98.14
7	Rules	96.92%	2.88%	95.62	97.12	99.66
8	RandomForest	97.02%	2.98%	97.15	97.02	97.80
9	NNge	97.02%	2.98%	97.15	97.02	97.80
10	Decorate	95.83%	4.17%	96.93	95.83	95.95
11	ClassificationViaRegression	95.54%	4.46%	96.28	95.54	96.11
12	FT	95.83%	4.17%	96.93	95.83	95.95
13	NB	95.83%	4.17%	96.93	95.83	95.95
14	RotationForest	95.83%	4.17%	96.45	95.83	96.45
15	LMT	96.73%	3.27%	97.13	96.73	97.30
16	MLP	97.02%	2.98%	97.31	97.02	97.64

Figure 2. Comparison of Bayes classifiers

Figure 3. Comparison of Functions classifiers

Figure 4. Comparison of Lazy classifiers

Figure 5. Comparison of various Meta classifiers

Figure 6. Comparison of various Tree classifiers

Figure 7. Comparison of various Rule classifiers

Figure 8. Comparison of Performance measures of best algorithmic models in 5 Classifiers

3. RESULTS AND DISCUSSION

A total of 59 models were used for classification of ischemic disease, and 16 models were found to be more efficient with accuracy when compared with the physician's diagnostic impression, gold standard and the kappa statistic (minimum of 0.736). The KSTAR algorithm showed the best diagnoses with the highest accuracy 97.32%, sensitivity 0.98, specificity 0.97, kappa 0.95 and ROC 0.995. The authors thus conclude that a CDSS can be developed to assist expert physicians in separating the positive and negative cases of heart disease. There was sensible agreement between the physician's diagnostic impression and the CDSS $k = 0.45$ ($p = 0.0008$). Sensitivity, specificity and accuracy are the commonly used statistical measures to illustrate the medical diagnostic test to enumerate how the test was good and consistent. Sensitivity evaluates the diagnostic test correctly at detecting a positive disease. Specificity measures how the proportion of patients without disease can be correctly ruled out. The association between both the sensitivity and specificity measures is defined by the graphical representation of the ROC curve, and this helps arrive at a decision to find the optimal model to determine the best threshold for the diagnostic test. Accuracy can be concluded with the aid of the sensitivity and specificity measures in the presence of prevalence.

Sensitivity = $TP / (TP + FN)$; Specificity = $TN / (TN + FP)$; Accuracy = $(TN + TP) / (TN + TP + FN + FP)$, where TN and TP are True Negatives and True Positives respectively. A comparison of 16 different best classifiers based on their performance measures; sensitivity, specificity, and accuracy are shown in Table 3.

Five AI techniques of classification (Bayes classifier, Function classifier, Meta classifier, Rule classifier, and Tree classifier) are used with a total of 59 models. The algorithms are run and parameters are obtained for further analysis. In the Bayes classifier, the WAODE classifier gives the best accuracy of 0.931. Table 1 illustrates the symptoms for heart disease identification. Figure 2 compares different algorithms of the

Bayes classifier on the basis of measures like sensitivity, specificity, accuracy, and precision. The WAODE algorithmic model is the best among the 7 algorithms in the Bayes Classifier with an accuracy of 93%. Figure 3 shows a comparison between the Multilayer Perceptron (MLP), Radial Basis Network (RBF), Simple Logistic Classifier, Sequential Minimal Optimisation, and Voted Perceptron. MLP shows the best accuracy of 97%. Figure 4 compares various measures between different lazy classifiers. KSTAR and IBK are equally better than the other three models with an accuracy of 97%. Figure 5 gives an overview of the Meta Classifiers.

Figure 6 shows the performance measures of various tree classifying algorithms. The two algorithmic models that are equally better are ID3 and Randomtree, with an accuracy of 97%. Figure 7 compares all models of the Rules Classifier. The best performer is the Nearest Neighbour like algorithm (NNge), with an accuracy of 97%. Even though the precision of the ZeroR model is 100%, its other performance measures are very low.

A comparison of the five best identified algorithms from each classifier type is displayed in Figure 8.

No studies investigating sudden deaths due to IHD without major tests like ECG, Stress tests, Cholesterol and Diabetes have been found in the literature. The literature includes various tests [23][24][25][26][27][28][29] for the identification of IHD. Through a systematic literature search, three incidence studies on CHD are identified within the Indian population [30]. The three incidence studies use different methods to attain data and so are not directly comparable. For a larger population, the need of the hour is to identify the IHD risk at the earliest and with a reduced number of feasible attributes. For this CDSS with attributes specially identified for the Indian population, diagnosis will be easier and quite manageable by experts, swiftly and efficiently. As variables for the measurement of social determinants of health depend on various factors like place of residence, race/ethnicity, gender, education, and socio-

economic studies [31], further studies with different population groups are necessary.

4. CONCLUSION

The preliminary results of the work suggest that IHD can be diagnosed using the CDSS. KSTAR segregates the negative and positive cases more appropriately than the other methods. Sensitivity and accuracy are better than the other methods. It is essential to continue studying classifier accuracy, including attribute selection for IHD, in order to develop an electronic protocol along with CDSS in future. This study may help people to determine their heart disease risk, as it involves a simple procedure for decision making in an effective way by extracting hidden knowledge from a historical database. In India, various climatic, environmental and habitual conditions may also influence this case. Samples collected from one area may differ from others and can result in diverse sensitivity and accuracy. Future work will focus on collection of data sets from diverse locations and comparison of the results.

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