Intelligent Decision Support for Real Time Health Care Monitoring System

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Abstract. In the health care monitoring, data mining is mainly used for classification and predicting the diseases. Various data mining techniques are available for classification and predicting diseases. This paper analyzes and evaluates various classification techniques for decision support system and for assisting an intelligent health monitoring system. The aim of this paper is to investigate the experimental results of the performance of different classification techniques for classifying the data from different wearable sensors used for monitoring different diseases. The Base Classifiers Proposed used in this work are IBk, Attribute Selected Classifier, Bagging, PART, J48, LMT, Random Forest and the Random Tree algorithm. Experiments are conducted on wearable sensors vital signs data set, which was simulated using a hospital environment. The main focus was to reduce the dimensionality of the attributes and perform different comparative analysis and evaluation using various evaluation methods like Error Metrics, ROC curves, Confusion Matrix, Sensitivity and Specificity. Experimental results reveal that the proposed framework is very efficient and can achieve high accuracy.

Keywords: Classification, Attribute Selected Classifier, Bagging, wearable sensors.

1 Introduction

There is growing need to supply constant Health Care Monitoring (HCM) and support to patients with Chronic Diseases (CD) especially the disabled, and elderly. Wireless sensor networks (WSNs) are used for gathering the information needed. The information may consist of many different sensors such as vital signs (e.g. heart rhythm or blood pressure), etc. Thus, most of the context information can be collected by distributed sensors throughout the environment and even the users themselves [1]. Sensors data is collected from disparate sources and later need to be classified and analyzed to produce information that is more accurate, more complete, or more insightful than the individual pieces. To deal with the large volume of data produced by these special kinds of wireless networks, one approach is the use of Data Mining

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techniques. Data mining plays a vital role in various applications such as business organizations, e-commerce, health care industry, scientific and engineering. In the health care industry, the data mining is mainly used for classification and predicting the diseases from the datasets. Various data mining techniques are available for predicting diseases namely Classification, Clustering, Association rules and Regressions. Classification is an important task in data mining. Classification of sensory data is a major research problem in WSNs. Woo et al. [2] proposed ECG signal monitoring system using body sensors. In the research used work One-class support vector machine classifier was used to detect abnormal heart signal values. Patel et al. [3] presented an approach to estimate the severity of symptoms based on accelerometer sensor data. The results of SVM based classification were compared and verified. Korel et al. [4], proposed context awareness Body area sensor network based health-monitoring system to detect abnormal episodes in the signal. Anthony et al. [5] proposed a research work used to recognize various activities of a user using a smart home. The data collected are classified using Multi class SVM and the result is compared for different kernel functions. Some Authors [6] proposed Classification Technique of Human Motion Context based on Wireless Sensor Network. Body sensor nodes are equipped with accelerometer; human motion will cause the waveform of the accelerometer to change accordingly. This change in waveform captured by sensor nodes is then analyzed by PCA (principal component analysis) and SVM (Support Vector Machine) method for clustering and classification. In this paper, Simulation Wearable sensors Data of vital signs are used for developing a decision support system. The rest of this paper is organized as follows. Section 2 describes the methods used for evaluation and the base proposed classifiers. Section 3 presents the Experimental Results and is analyzed in Section 4 followed by discussions in Section 5.

2 Computational Intelligence

2.1 Base Classifiers Used

A) Decision tree algorithm J48

J48 classifier is a simple C4.5 decision tree for classification. It creates a binary tree. The decision tree approach is most useful in classification problem. With this technique, a tree is constructed to model the classification process. Once the tree is built, it is applied to each tuple in the database and results in classification for that tuple [8-9].

B) Logistic Model Trees (LMT)

A logistic model tree (LMT) [10] is an algorithm for supervised learning tasks, which is combined with linear logistic regression and tree induction. LMT creates a model tree with a standard decision tree structure with logistic regression functions at leaf nodes. In LMT, leaves have a associated logic regression functions instead of just class labels.

C) Random Forest

Random forest [11] is an ensemble classifier that consists of many decision tree and outputs the class that is the mode of the class's output by individual trees. Random Forests grows many classification trees without pruning. Then each decision tree classifies a test sample and random forest assigns a class, which have maximum occurrence among these classifications.

D) Random Tree

A random tree is a tree formed by stochastic process. Types of random trees include Uniform spanning tree, Random minimal spanning tree, Random binary tree, Random recursive tree, Treap, Rapidly exploring random tree, Brownian tree, Random forest and branching process [12].

E) Meta-learning

Meta-learning is about learning from learned knowledge [13]. The idea is to execute a number of concept learning processes on a number of data subsets, and combine their collective results through an extra level of learning. Meta-learning aims to compute a number of independent classifiers by applying learning programs to a collection of independent and inherently distributed databases in parallel. The “base classifiers” computed are then collected and combined by another learning process. The most popular meta-learning algorithms are bagging and boosting. Bagging [14] is a method for generating multiple classifiers (learners) from the same training set. The final class is chosen by, e.g., voting.

F) PART

Rule-based learning, especially decision trees (also called classification trees or hierarchical classifiers) is a rule generator that uses J48 to generate pruned decision trees from which rules are extracted [15].

G) IBK

The lazy IBk (commonly known as K- nearest neighbor) is one of classification algorithms that uses distance weighting measures with capability of various attributes like Date attributes, Numeric attributes, Unary attributes, Nominal attributes, Missing values, Binary attributes and Empty nominal attributes. K-nearest neighbours classifier can select appropriate value of K based on cross-validation and also do distance weighting [16-17].

2.2 Attribute Selection

It is often an essential data processing step prior to applying a learning algorithm. Reduction of the attribute space leads to a better understandable model and simplifies the usage of different visualization technique. Attribute selection reduces dataset size by removing irrelevant and redundant attributes. It finds a minimum set of attributes such that the resulting probability distribution of data classes is as close as possible of original distribution. Attribute evaluator method and the search method Best first evaluates the worth subset of attributes by considering the individual predictive ability of each attribute [18]. In the preprocessing step, we have changed the class attribute to Abnormal or Normal where an 'Abnormal' specifies class 1 and a 'Normal' Specifies class 0.

2.3 Cross-Validation Method

In this paper, we applied a 10-fold cross validation test option. Cross-Validation (CV) is a statistical method of evaluating and comparing learning algorithms by dividing data into two segments: one used to learn or train a model and the other used to validate the model. The basic form of CV is k-fold CV. In k-fold CV the data is first partitioned into k equally (or nearly equally) sized segments or folds. Subsequently k iterations of training and validation are performed such that, within each iteration a different fold of the data is held-out for validation while the remaining k -1 folds are used for learning. The advantage of K-Fold Cross validation is that all the examples in the dataset are eventually used for both training and testing.

2.4 Methods Used for Evaluation of Algorithms

We evaluate our classifiers by measuring their performance by various methods and performance matrices. The following methods are used in our experiments.

- Evaluation of time to build a model for each classifier.
- Mean Absolute Error (MAE):
- Root Mean Squared Error (RMSE)
- Kappa Statistics (KS)
- ROC curves. Additionally the AUC (Area Under ROC Curve) is taken under consideration.
- Confusion Matrix

3 Experimental Results

3.1 Data Set and Simulation of Hospital Environment

We simulated the environment of Baraha Medical City in Shambat, Khartoum North, Sudan using the framework reported in [23-24]. It is situated in a 600 Sq. meter lot with a garden within the compound. The hospital has five floors with a 75-bed capacity and provides complete medical services for patients. The Hospital receives patients who suffer from chronic diseases such as heart diseases, asthma, diabetes and abnormal blood pressure etc. Also people in post-surgery state needs continuous monitoring of their health condition, especially the vital signs, until their health status becomes stable. In our simulation, we allocated 6 chronic ill patients in each floor (total 30 patients) as we focused only on the monitoring and providing medical service for patients with chronic or terminally ill diseases. Depending on the critical condition of the patent, each patient was attached with several sensors. For thirty patients, there were a total of 300 readings at any measuring instant. Depending on the criticality of the patient's condition, when a sensor finds values that fall in the danger zone an automated alarm is triggered notifying the nurses and doctors through mobile network or Wifi systems [23]. In this project, our main task is to develop a decision support system that could assist the hospital management to assess the situation of the hospital as Normal or Abnormal (too many medical emergencies) so that more medical help could be sorted.

We apply attribute selection method to reduce the number of the attributes. All 300 attributes were labeled as *A, B, C, Z, …*and *KN*. We investigated several classifiers using WEKA [7] and finally managed to reduce to 6 attributes: *AK, CM, CP, CW, FJ* and *KN*. We found that cross-validation give the best classification with 10 Fold. Then the overall accuracy for all classifiers was done. We selected classifiers with classification accuracy between 90% to 100% as the proposed Base Classifiers. The Base Classifiers Proposed in our investigation in this paper are IBk, Attribute Selected Classifier, Bagging, Random Committee, PART, J48, LMT, Random Forest, Random Tree. The aim of this paper is to investigate the experimental results of the performance of different classification techniques for the simulation wearable sensors dataset. The performance factors used for analysis are accuracy and error measures. The accuracy measures are TP rate, F Measure, ROC area, Sensitivity and Specificity. The error measures are Mean Absolute Error, Root Mean Squared Error and Kappa Statistics. In the preprocessing step we have changed the class attribute to Abnormal or Normal where a ‘Abnormal’ specifies 1 class and a ‘Normal’ Specifies 0 class. Table 1 depicts the various error metrics analyzed in the data set. It is inferred from Table 1 that Random Tree has the least MAE and highest Kappa Statistic value. Random Tree is an appropriate model for classifying the hospital situation in a minimal span of time with higher accuracy.

Table 1. Performance Measures comparison

Algorithm	MAE	RMSE	KS	Correctly Classified
IBk	0.0978	0.3104	0.8062	673 90.3356 %
Attribute Selected Classifier	0.1008	0.2631	0.8384	685 91.9463 %
Bagging	0.1527	0.2609	0.8089	674 90.4698 %
Random Committee	0.0643	0.1931	0.9004	708 95.0336 %
PART	0.101	0.264	0.8355	684 91.8121 %
J48	0.0865	0.2518	0.8574	692 92.8859 %
LMT	0.0854	0.2454	0.844	687 92.2148 %
Random Forest	0.0961	0.219	0.8843	702 94.2282 %
Random Tree	0.051	0.2258	0.8977	707 94.8993 %

Table 2. Classifier performance in term of recall precision, *f* measure and false alarm rate

Algorithm	Recall	Precision	F-measure	False alarm rate
IBk	0.916	0.905	0.911	0.085
Attribute Selected classifier	0.914	0.914	0.913	0.076
Bagging	0.893	0.905	0.898	0.084
Random Committee	0.938	0.957	0.947	0.038
PART	0.924	0.908	0.914	0.080
J48	0.9185	0.9316	0.924	0.061
LMT	0.905	0.9316	0.917	0.062
Random Forest	0.927	0.951	0.938	0.044
Random Tree	0.9383	0.9544	0.945	0.041

As an example of classifier error illustration, Figure 1 depicts the Classifier error of Random Committee. The blue crosses indicate the Normal class and red crosses indicate the Normal class and squares indicate not classified. Table 2 depicts the classifier performance of each classifier in term of recall precision, *f* measure and false alarm rate. It is inferred from that Random Committee model has the highest precision and lowest false alarm rate, and the same recall as Radom Tree. Table 3 depicts the algorithm performance of each classifier in term of recall precision and *f* measure for Normal class is summarized. It is inferred from Table 3 that Random Committee model has the highest precision and also high recall. Figure 2 depicts the Area under ROC of Random Committee classifier with highest area under Roc. Tables 4 depict the classifier performance of each classifier in term of recall precision, and f measure for abnormal class is summarized. It is inferred from Table 4 that Random Committee model has the highest precision. Table 5 depicts the classification performance of each classifier in term of Sensitivity and Specificity with the Random Committee model having the highest Specificity and also high Sensitivity. Random Committee model also has the highest accuracy and the IBK model has the lowest accuracy.

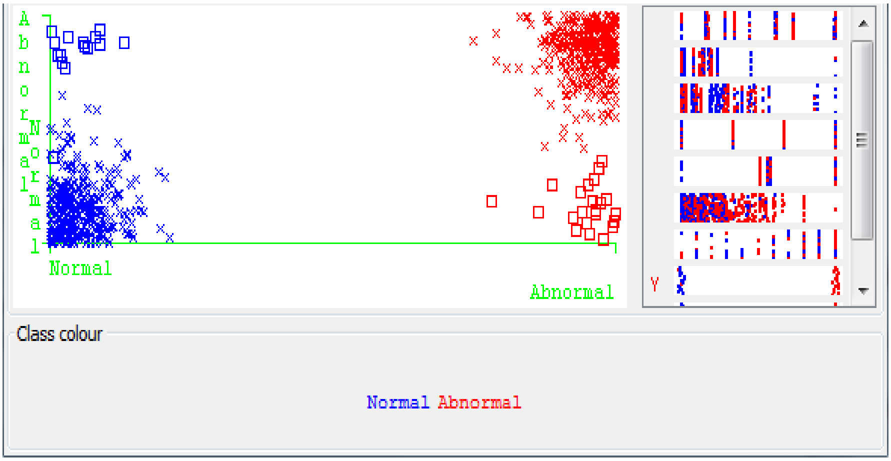

Fig. 1. Classifier error of Random Committee

Table 3. Classification performance for Normal class

Classifiers	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
IBk	0.883	0.109	0.878	0.883	0.881	0.891
Attribute selected classifier	0.906	0.122	0.869	0.906	0.887	0.926
Bagging	0.880	0.112	0.875	0.880	0.878	0.953
Random Committee	0.943	0.071	0.922	0.943	0.932	0.984
PART	0.926	0.124	0.869	0.926	0.897	0.955
J48	0.903	0.109	0.881	0.903	0.892	0.934
LMT	0.886	0.094	0.894	0.886	0.890	0.948
Random Forest	0.937	0.084	0.909	0.937	0.923	0.973
Random Tree	0.932	0.074	0.919	0.932	0.925	0.929

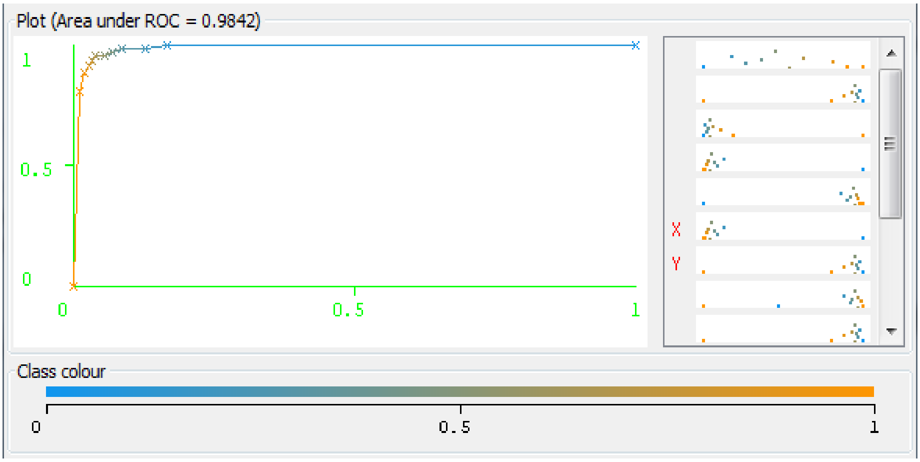

Fig. 2. Area under ROC of Random Committee classifier

Table 4. Classification performance of each classifier for abnormal class

Classifiers	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
IBk	0.901	0.094	0.915	0.901	0.908	0.910
Attribute selected classifier	0.878	0.094	0.913	0.878	0.895	0.926
Bagging	0.888	0.120	0.893	0.888	0.891	0.953
Random Committee	0.929	0.057	0.948	0.929	0.938	0.984
PART	0.876	0.074	0.930	0.876	0.902	0.955
J48	0.891	0.097	0.912	0.891	0.901	0.934
LMT	0.906	0.114	0.899	0.906	0.903	0.948
Random Forest	0.916	0.063	0.943	0.916	0.929	0.973
Random Tree	0.926	0.068	0.938	0.926	0.932	0.929

Table 5. Classification performance of each classifier in term of Sensitivity and Specificity

Classifiers	Sensitivity	Specificity	Accuracy
IBk	0.8907	0.914	0.9033
Attribute Selected Classifier	0.941	0.923	0.9194
Bagging	0.8932	0.915	0.9046
Random Committee	0.938	0.961	0.9503
PART	0.924	0.92	0.9221
J48	0.918	0.938	0.9288
LMT	0.905	0.937	0.9221
Random Forest	0.927	0.955	0.9422
Random Tree	0.938	0.958	0.9489

4 Discussions

Empirical results indicate that the execution time of Random Committee algorithm is lowest for classification in comparison with the rest of classification algorithms, and the LMT algorithm has the higher execution time. The MSE error of the classification values for Random Committee is lower in comparison with the rest of the based proposed classifiers, and the Meta bagging classifier has higher MSE error in comparison with the rest of the base proposed classifiers. In terms of recall precision, f measure and false alarm rate the Random Committee model has the highest precision and lowest false alarm rate, and the same recall as Random Tree. In term of recall precision and f- measure for Normal class it is inferred that Random Committee model has the highest precision and also high recall. With higher true positive rate and minimum false rate also with higher ROC Area when the classification is Normal class in comparison of the rest of the classifiers. Attribute Selected Classifier has the lower precision in comparison with the rest. Also from the performance of each classifier in term of recall precision and f measure for abnormal class, Random Committee model has the highest precision and also high recall (with higher true positive rate and minimum false rate), also has highest ROC Area in comparison with other classifiers. While PART classifier has the lowest precision the same as Attribute Selected Classifier but with highest in ROC Area compare with Attribute Selected Classifier. From Sensitivity, Specificity and Accuracy perspective, the Random Committee model has the highest Specificity and also high Sensitivity the same as Random Tree but with highest accuracy of all the classifiers. While IBK classifier has the lowest Sensitivity, Specificity and Accuracy compare with the rest of the classifiers. To sum up, from the execution and accuracy point of view, Random committee model can be identified as the best choice for analysis and detection model among all the other classifier algorithms. Random committee provides an advantage that with a reduced feature set a better classification performance and is able to offer a better decision support system.

5 Conclusions

The main goal of this paper is to evaluate nine based classifier algorithms to develop a decision support system to classify the situation of an emergency hospital based on the Vital Signs from Wearable Sensors. We reduced the number of attributes from 300 attributes to 6 attributes. We explored and evaluated the models with various methods of evaluation based on Error Metrics, ROC curves, Confusion Matrix, Sensitivity and Specificity. We compared the performance of the entire classifiers and empirical results illustrate that Random committee classifier with selection attribute method gives better accuracy, error rate and reduced false alarm rate and with the highest Sensitivity and Specificity.

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