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Research Paper

Comprehensive study on ensemble classification for medical applications

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Abstract

The aims of this paper were to provide a comprehensive review of classification techniques and their alternative approaches in data mining. Classification is a data mining technique that assigns categories to a collection of data to aide in more accurate predictions and analyses. It is one of the several methods intended to make the analysis of very large datasets effective. The goal of classification is to accurately predict the target class for each case in the data. One of the classification approaches is the ensemble method. In recent years, the usage of ensemble method in medical application has been increasing. Not only in medical areas, it can also help researchers to solve modem problems in many fields like machine learning, data mining and other related areas.

Keywords: *Classification; Single Classification; Ensemble Methods; Medical Application.*

1. Introduction

Data mining is the application of specific algorithms for extracting patterns from data [16]. It is clarified as one set of activities used to discover new, hidden or unexpected patterns in data [52]. It must be meaningful in order to create some advantages, especially for the economy [62]. For example, healthcare transactions contain a huge amount of data. It is very complex and voluminous to be processed and analysed by traditional methods. Data mining provides the methodology and technology to transform these mounds of data into useful information for decision-making. The most common and important applications in data mining probably involve predictive modelling. One of the predictive modelling is classification technique [21].

Classification is a data mining method utilised to foresee gathered participation for information occasions. It is competent to prepare and develop a more extensive assortment of data than relapse in popularity [39]. Classification comprises of predicting a certain result based on a given input. In order to predict the result, the algorithm processes a training set containing a set of attributes and particular results as a rule called objective or prediction attribute [60].

One of the classification tasks is ensemble methods. It constructs a predictive model by integrating numerous models [44]. It can be utilised for improving prediction performance. In [45], the ensemble method was characterised as a combination set of models, each of which does the same assignment to make the accuracy and reliability decisions on a dataset that can be attained better than a single model. These strategies are very popular in medical areas such as classifying medical images and diagnosing diseases.

In [12], a different classifier system was utilised to classify pictures based on classes of typical body cells, infected cells and highly infected cells in order to categorise medical images. Moreover, this approach is utilised on breast cancer determination to know which is the most suitable combination approach for each on dataset [47], [49].

The rest of this paper is organised as follows. Section 2 discusses the types of classification, followed by the reviews of the ensemble in medical application as shown in section 3 and summarises the classification algorithms to medical applications as shown in section 4. Lastly, the conclusions are stated in section 5.

2. Classification

Classification models known as predictive methods require the data to be incorporated in a special class attribute [4]. Classification predicts categorical labels, while the prediction models continue the valued functions. Classification is the assignment of generalising known structure to apply to modern data [10]. Classification tasks are partitions of two parts, which are single classification and multi-classification or known as an ensemble.

2.1. Single classification

Classification comprises of conveying a class label to a set of unclassified cases. Supervised classification is the set of possible classes known in advance, while unsupervised classification is the unknown set of possible classes [13]. A few major classification methods include decision tree induction, Bayesian networks, k-nearest neighbour classifier, case-based reasoning, genetic algorithm and fuzzy logic techniques [39]. Single classification is not only used in the medical field but also in the environmental field. In [52], data mining techniques like artificial neural network, back propagation, MLP, GRNN and decision tree were used in predicting water quality. The different classifiers such as decision tree (J48), multi-layer perception (MLP), Naive Bayes (NB), sequential minimal optimisation (SMO) and instance based for K-Nearest neighbour (IBK) on three different databases of breast cancer

(Wisconsin Breast Cancer (WBC), Wisconsin diagnostic breast cancer (WDBC) and Wisconsin prognostic breast cancer (WPBC)) were compared to find the best classifier for each of the breast cancer datasets by using classification accuracy and confusion matrix based on the 10-fold cross validation method [49]. A particular classifier may be much better than others for a particular dataset but another classifier could perform much better for a few other datasets [7].

2.2. Ensemble/multi-classification

Ensemble methodology is used to build a predictive model by integrating multiple models. It is well-known that ensemble methods can be used for improving performance. Researchers from different disciplines such as statistics and artificial intelligence have considered the use of ensemble methodology [46]. Ensemble methods for supervised machine learning have become popular due to their ability to accurately predict class labels of simple and lightweight “base learners” groups. Researchers from various disciplines such as statistics, pattern recognition and machine learning have seriously explored the use of ensemble methodology [45]. Ensemble method leads to improved accuracy compared to a single classification or regression model [36]. In [57], they also stated that classifiers ensemble can effectively improve classification performance than a single classifier. The implementation of ensemble mapping techniques showed higher accuracy than any single model, where the yields of numerous models are combined [45]. Ensemble models use a combination of several hypotheses, which tend to cancel out overfitting errors [14]. In [18], ensemble classifiers were always found to outperform single decision tree classifier in having greater accuracies and smaller predicting errors when applied to a pancreatic cancer proteomic dataset. Other applications of ensemble classifiers are used in data quality assessment sensor, shellfish farm closure prediction and cause identification, handwriting recognition, benthic habitat mapping, dealing with missing sensor data and algae growth prediction [43]. Ensemble models are separated into two classes which are homogeneous and heterogeneous.

2.2.1. Homogeneous ensemble classifier

Homogeneous ensemble consists of members having a single-type base learning algorithm. In this case, ensemble members can be distinctive by the structure [14]. In [3] presented a novel weighted ensemble scheme which intelligently combines multiple training algorithms to increase the Artificial Neural Networks (ANN) forecast accuracies. Homogeneous techniques use a single algorithm and achieve diversity through some forms of variability in the data (e.g., randomisation) [17].

2.2.2. Heterogeneous ensemble classifier

Heterogeneous ensemble comprises of members having distinctive base learning algorithms [14]. It is created based on ten different classifier algorithms [6]. As an example, in [14], one heterogeneous ensemble model having PCA-based CI models of type MLP, SVR and ANFIS was created. At first, the input in MLP was provided. The poorly predicted training data by MLP was chosen and provided to train the SVR and later on the poorly predicted training data by SVR to ANFIS for training. In [31], heterogeneous ensemble was referred to a classifier constructed or learned from an ensemble of distinctive sorts of classifiers. It is also known as hybrid ensemble classifiers.

2.3. Classification performance measurement

The classification performance measurement is listed below.

2.3.1. Accuracy

The accuracy metrics were calculated with the help of a Machine Learning - Confusion Matrix that presents on Table 1.

Table 1: Confusion Matrix

	Predicted a	Predicted b
Real a	TP	FN
Real b	FP	TN

With classification of performance measurement, the calculation of classification accuracy is measured by (1).

$$\text{Accuracy} = (TP+TN) / (TP+FN+FP+TN) \quad (1)$$

where TP is the number of positive instances correctly classified. TN is the number of negative instances correctly classified. FN is the number of positive instances incorrectly classified as negative. FP is the number of negative instances incorrectly classified as positive [35].
Accuracy is not really a reliable metric for the real performance of a classifier when the number of samples in different classes varies greatly (unbalanced target) because it will yield misleading results. For example, if there were 95 cats and only five birds in the dataset, the classifier could easily be biased into classifying all the samples as cats. The overall accuracy would be 95% but in practice, the classifier would have a 100% recognition rate for the cat class but a 0% recognition rate for the bird class.

2.3.2. Misclassification rates

The error or misclassification rates are good complementary metrics to overcome this problem. The performance of a model can be expressed in terms of its error rate, which is given by (2):

$$\text{Error rate} = (FP+FN) / (TP+FN+FP+TN) \quad (2)$$

Error rate is used to measure the fusion of classifiers in WQ Dataset [48]. In [8], all of the classification algorithms derived the decision boundaries with the goal of minimising the misclassification rate of the training data.

2.3.3. Sensitivity and specificity

The other four performance indicators (TPR, TNR, FNR and FPR) help providing detailed performance for each class and are more realistic tools for comparing the performance of the predictive models [26].

$$\text{True Positive Rate, TPR, Sensitivity} = TP / (TP + FN)$$

$$\text{True Negative Rate, TNR, Specificity} = TN / (TN + FP)$$

$$\text{False Positive Rate, FPR} = FP / (TN + FP)$$

$$\text{False Negative Rate, FNR} = FN / (TP + FN)$$

2.3.4. Precision and recall

In order to test the classification ability of the model, several evaluation measures (such as precision, recall and F-measure) can be used [59].

$$\text{Precision, } p = TP / (TP + FP)$$

$$\text{Recall, } r = TP / (TP + FN)$$

$$F_1\text{measure} = 2rp / (r + p) = 2 \times TP / (2 \times TP + FP + FN)$$

In [34], precision, recall and F-Measure (F1) metrics were used to determine accuracy since the majority of patient data (85-99 %) consisted of normal EEG. Furthermore, precision and recall were used to measure the performance of shapely value embedded genetic algorithm called as SVEGA that improved the breast cancer diagnostic accuracy which selected the gene subset from the high dimensional gene data [51].

2.3.5. Receiver operator characteristics (ROC)

ROC curves, although constructed from sensitivity and specificity, do not depend on the decision threshold. In an ROC curve, every possible decision threshold is considered. An ROC curve is a plot of a false-positive rate (FPR) test or 1 – specificity (plotted on the horizontal axis), versus its sensitivity (plotted on the vertical axis) [20].

3. Ensemble in medical application

Nowadays, modern hospitals are well-prepared with monitoring and other data collection devices resulting in enormous data, which are collected persistently through health examination and medical treatment. All these have driven to the fact that medical area progressively produces voluminous amounts of electronic data which are getting more complicated. Before the existing of data mining, various statistical methods have been utilised for modelling in the area of disease diagnosis. Presently, it is more or less demanding since data mining has been proven as more powerful and effective in discovering useful pattern from a large dataset [5].

4. Classification algorithms applied to medical applications

Table 2 presents the classification algorithms used in medical applications.

Table 2: Classification Algorithms Applied To Medical Applications

Algorithms used	Performance Measurements	Dataset	References
Naïve Bayesian classifier, Hybrid feature selection algorithm (CHI-WSS)	classification accuracy (or error rate), ROC	medical datasets	[1-2, 5]
Decision tree (J48), Multi-Layer Perception (MLP), Naive Bayes (NB), Sequential Minimal Optimization (SMO) and Instance Based for K-Nearest neighbor (IBK)	accuracy and confusion matrix	breast cancer (Wisconsin Breast Cancer (WBC), Wisconsin Diagnosis Breast Cancer (WDBC) and Wisconsin Prognosis Breast Cancer (WPBC)	[49, 51]
Gauss-Newton representation based algorithm (GNRBA)-pattern recognition	classification accuracy, sensitivity, specificity, confusion matrices, a statistical test and the area under the receiver operating characteristic (AUC)	Wisconsin Breast Cancer Database (WBCD) and the Wisconsin Diagnosis Breast Cancer (WDBC)	[11]
Clustering, Classification and Regression Trees (CART)	Accuracy	Wisconsin Diagnostic Breast Cancer and Mammographic mass datasets	[25, 32]
Rough set, Kth–nearest neighbor, support vector machine, Back propagation algorithm, multilayer perceptron	disease prediction and diagnosis	Medical dataset	[22]
Feedforward artificial neural network	Segmentation, accuracy	tumor echocardiograms	[56]
Linear discriminant analysis, support vector machine, K-means, K-nearest neighbor	specificity and sensitivity	prostate cancer	[15]
K-Nearest Neighbor and Support Vector Machine	classification performance	multispectral brain magnetic resonance images	[29]
Naive Bayes, Support Vector Machine (SVM), Boosted Trees and Random Forests classifiers	accuracy, sensitivity, specificity and area under ROC)	Parkinson's Disease (PD)	[42]
Five artificial intelligence techniques, namely decision trees, Bayesian inference, k-nearest neighbor algorithm, support vector machines and artificial neural networks	accuracy, sensitivity, specificity and area under the ROC curve (AUC)	Celiac disease	[58]
Support vector machines (SVMs)	Accuracy	lung cancer patients breast cancer	[27, 40, 63]
Logistic regression, artificial neural networks (ANNs) and decision tree	Accuracy, sensitivity and specificity	diabetes or prediabetes	[28]
Different multilayer perceptron	Error, sensitivity and specificity	Lung nodule data	[37]
ADTree, BFTree, DecisionStump, FunctionalTrees (FT), J48graft, LADTree, LMT, Random Forest, Random Tree, REPTree	Accuracy, AUC	Wisconsin data set	[55]
Random forest ensembles	sensitivity/specificity	Alzheimer's disease data set	[24]
Nine k-nearest neighbor cross-validated classifiers	Accuracy	datasets of post-stroke gait	[23]
AdaBoost J48 classifier algorithm) and meta-learning (k-means algorithm)	decision-making and patients' record management tasks.	Hepatitis, hypothyroid and diabetes EHRs	[30]
Locality-constrained Subcluster Representation Ensemble (LSRE) model	classify high-resolution computed tomography (HRCT) images of interstitial lung diseases (ILDs)	interstitial lung diseases (ILDs)	[54]
Support Vector Machines (SVM), Bagging using the RPART function (BAG), Random Forest (RF) and Naıve Bayes (NB)	Area Under the Curve (AUC), sensitivity (Patient), and false positive (FPR) rate (instance)	Medical data	[9]
Bayes Net, SVM, Logistic, SGD, Simple Logistic, SMO, K*, J48 and RF	Accuracy	Hepatitis data set	[13]

Bayes classifier, regression model	Accuracy	Sleepapnoea–Hypopnoea Syndrome (SAHS)	[41, 53]
Adaboost ,bagging, J48 (c4.5) decision tree	ROC	Diabetic data set	[38]
Adaboost, ensemble classifier	Computer-aided diagnosis	Lung Image dataset	[33]
League Championship Algorithm Optimized Ensembled Fully Complex valued Relaxation Network (LCA-FCRN)	Accuracy	Breast cancer	[50]
Combination of Dimensional Reduction and Data Mining Techniques	Accuracy and the number of reduced attributes	Heart Disease	[61]
Artificial Neural Network Based Fast Edge Detection Algorithm	Image quality	MRI Medical Images	[19]

5. Conclusion

Supervised learning includes classification as one of the most significant brands in data mining with a recognised output variable in the dataset. Classification methods can achieve high accuracy in classifying mortality cases. They are divided into two categories which are single and multi-classifiers/ensembles. In medical diagnoses, the role of data mining approaches has increased rapidly. Classification algorithms are very helpful in classifying the data, which are important in the decision-making process for medical practitioners. Furthermore, the various pre-processing techniques of classifier accuracy and multi-classifiers techniques were developed. Based on a survey, multi-classifier methods achieved better accuracy than the single ones. As a future research work, it is intended to apply deep learning concept on ensemble methodology in improving the accuracy performance of dataset.

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