Paper from: *Data Mining III*, A Zanasi, CA Brebbia, NFF Ebecken & P Melli (Editors).
ISBN 1-85312-925-9

Making the most of data in order to provide accurate clinical decision support systems for the use in the determination of heart disease

K.E. Burn-Thornton
DATA MINING GROUP, Dept. Computer Science, Durham University, Durham, UK.

Abstract

This paper provides a description of the results of investigations into the effect of the nature of ECG data, on the classification accuracy of patient state which a Clinical Decision Support System (DSS), based upon the data (knowledgebase), is able to provide.

These results show that changes in classification accuracy of 40% can be achieved by changing both the size, and stratification bias, of the knowledgebase. The results suggest that use of a CDSS can be employed to aid an inexperienced physician in the classification of patients with heart disease as long as careful consideration is given to the size, and stratification bias, of the data comprising the knowledge base used to support the DSS.

1 Introduction

The current demands placed upon the health service in this country are resulting in not only, a diminishing time being taken to attempt to accurately predict from the ECGs whether or not heart disease is present but also, the reliance on the less experienced team members to make an accurate decision regarding current patient state.

If a decision support system could be provided, with a similar accuracy of patient classification to that shown by 'experts' (consultants), not only could 'expert' made diagnosis be confirmed but also those less experienced team members could use the CDSS to support their patient classification.

Paper from: *Data Mining III*, A Zanasi, CA Brebbia, NFF Ebecken & P Melli (Editors).
ISBN 1-85312-925-9

Our previous work using Data Mining to provide the underpinning technology for CDSSs suggest that Data Mining has the potential to provide the underpinning technology for CDSS for patient state predication in this context [1]. This paper, an extension of the previous work, presents the results of an investigation of how the nature of the knowledgebase supporting the CDSS effects the accuracy of patients state classification afforded by use of the CDSS.

In this paper the results of initial work are described regarding the use of varying sizes of 'ECG' data sets of varying stratification biases and their effect on accuracy of patient state classification as well as the potential impact on support given to less experienced physicians if they were being used to provide the knowledge base in a CDSS.

The first section provides an overview of the requirements for CDSSs to support less experienced physicians in the analysis of ECG data. This is followed by a brief discussion regarding the choice of Data Mining algorithms available for creation of the model on which the CDSS relies and the applicability of different classes of algorithm to different data types. This is followed by a description of the methodology used to perform analysis of the data. The results of the analysis of the data are then detailed along with a discussion of the results. Conclusions and Future Work are then discussed.

2 ECG decision support

The use, and interpretation, of 12-lead ECGs is still used as an instant, reliable, indicator of whether heart disease is present in patients experiencing any of the symptoms of heart disease – such as chest pain

12 leads are attached to patient who is suspected to have suffered from acute myocardial infarction [2] and the 12-lead traces, a record of a time varying potential difference across the heart, are analyzed in order to determine whether the patient is suffering from acute myocardial infarction. However, the task of interpretation of the traces is one, which relies on the type of judgement gained by experience. Less experienced physicians may not be as well placed, as their older colleagues, to correctly classify the patient state because they have observed fewer ECG traces fewer patients – in other words they are less experienced.

Clinical Decision Support Systems (CDSSs) can be taught the experience learnt over many years by an experienced physician (or physicians) and hence they should be able to provide the support required by the younger, less experienced, physicians.

A CDSS can be taught (trained in) the knowledge of experienced physicians by the use of a knowledge base (and the model created from it) which is, in effect, the summation of the results of patient state diagnosis, from 12-lead ECGs, by experienced physicians. When the CDSS is presented with an ECG trace, taken from a patient in casualty, it can then use the knowledge base (what is has been taught) to predict the patient state and hence support the less experienced physician.

Paper from: *Data Mining III*, A Zanasi, CA Brebbia, NFF Ebecken & P Melli (Editors).
ISBN 1-85312-925-9

The accuracy of the support provided by the CDSS (or the model created) depends upon the accuracy of the knowledgebase i.e. the accuracy of the patient classification carried out by the experienced physicians, the algorithm (or algorithms) used to create the model and the size & stratification bias of the knowledgebase.

As data miners we have no control over the accuracy of patient classification – apart from using experienced, respected, physicians. However, we can control the algorithm(s)and data used to create the model on which the CDSS will depend. The next section discusses suitable algorithms to use for creation of the model with the following sections detailing the investigations which have been carried out to determine the effect of size, and stratification bias, of the data base upon the accuracy of patient state.

3 Suitable algorithms: data mining algorithms

Many of the CDSSs created rely on neural networks for interpretation of the clinical data [2-3]– i.e. neural networks are used to provide the machine intelligence. However, despite the obvious diagnostic advantages of the use of neural networks for clinical diagnosis, in their simplest form they do not provide the reason for diagnosis which can provide important decision support for the inexperienced physician.

Data Mining techniques [4], and Data Mining algorithms [4], appear to offer the solution to the shortcomings of the neural network technique because not only, do many data mining algorithms have the potential of being able to interpret the clinical data but also, many can detail the rules used for diagnosis to the physician. This is valuable both in a decision support and learning context to the inexperienced physician.

Each data mining algorithm, or class of algorithms, performs most accurately over certain characteristic data sets such as numerical or categorical with many or few variables and many, or few classes. This was borne in mind during the choice of algorithms for these investigations. Consequently the algorithms chosen for these investigations were determined after with a prior knowledge that the data being analysed was numeric data with a small number of classes and a relatively small number of variables.

The algorithms chosen were k-NN, C4.5, CN2, RBF, and OC1. Information regarding the nature of the algorithms can be found elsewhere [4]. The algorithms belong to the statistical, machine learning (both decision tree and rule induction), neural networks, and hybrid classes respectively.

4 Methodology

The data used in these investigations consisted of 12-lead ECG data collected from 11,000 patients. 12 key features were extracted from the data to create the 'original' data set of 11,000 patient samples containing 12 'numeric' variables.

Paper from: *Data Mining III*, A Zanasi, CA Brebbia, NFF Ebecken & P Melli (Editors).
ISBN 1-85312-925-9

8 'stratification' sub-sets were created from these 11,000 samples. These sub-sets ranged in stratification bias from 1:1/2 to 1:5 with sample size ranging between 1550 and 5170 samples (sets 9-16)[2].

All investigation sets were then split in the ratios 19:1, 18:2, 17:3, 16:4, 15:5, 14:6, 13:7, 12:8, 11:9,10:10 resulting in 80 sub-sets. This enabled the data mining algorithms to be effectively trained on the data of the larger sub-set and then tested on the data from the smaller sub-set.

The training data was then used to train all five of the algorithms. After training the algorithms were tested in their accuracy of determination of patient state. Time to perform classification was also recorded.

All of the investigations outlined above were repeated 10 times to ensure that the results obtained were repeatable and valid. A mean average value of the 10 'runs' is shown in Graphs 1-5.

5 Results

Graphs 1-5 show the variation in classification accuracy with size for a varying stratification bias.

Graphs 1-5 show that the classification accuracy of all algorithms falls as the stratification bias falls with changes of classification accuracy of between 13 and 40% being observed. All graphs show distinct behaviour for the different stratification biases. OC1 appears to be the most sensitive algorithm to changes in stratification bias with a change of 40% classification accuracy being observed between the high and low stratification sets.

(Sets 1-7 form the basis of the ongoing work which is briefly outline in the Future Work Section).

Paper from: *Data Mining III*, A Zanasi, CA Brebbia, NFF Ebecken & P Melli (Editors).
ISBN 1-85312-925-9

6 Conclusions and future work

The sensitivity of classification accuracy of all algorithms to a change in stratification bias suggests that care has to taken in the choice of knowledgebase used to underpin a CDSS for supporting diagnosis of heart disease using ECG traces. This is especially so if OC1 is used with its classification accuracy increasing by 40% as the stratification bias increases from 1: 5 to 1:1/2.

The size of data set required for the knowledgebase, and stratification bias, could be selected with an acceptable classification accuracy in mind. This choice could be made using the curves of Figures 1-5 as guidance.

Future Work, currently in progress, is investigating effect of varying the stratification bias of the set whilst keeping the size constant. Initial work suggests that this does cause a change in classification accuracy but that the change in classification accuracy caused by stratification bias and size of set can be separated.

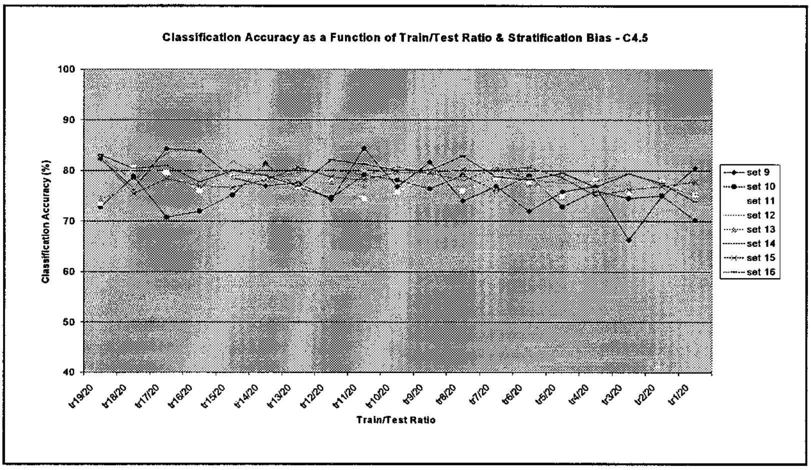
7 Acknowledgements

Acknowledgement is made to Simon Thorpe and Mattias Ohlsen for their contribution to this work and the Clinical Physiology Department at Lund University for the provision of this data.

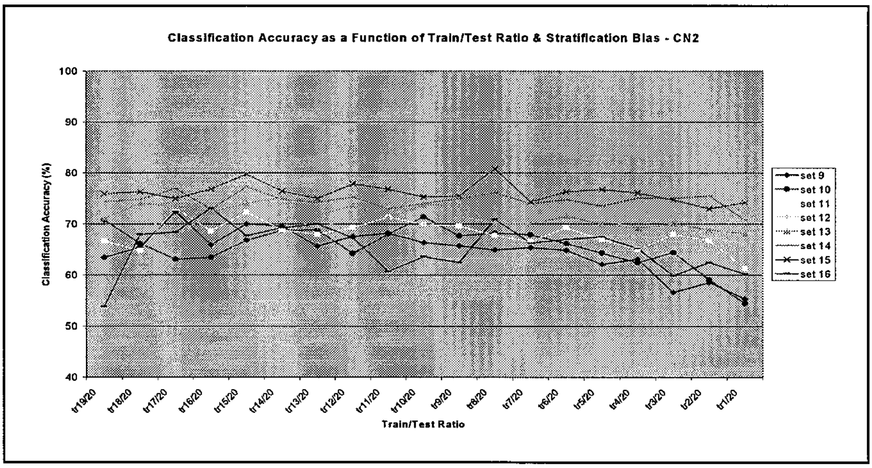
References

1. Burn-Thornton KE, Edenbrandt L: Pinpointing the Key Indicators of 12-lead ECGs Using data mining. Computers & Medicine. Aug 1998.
2. Mulholland G, Brewer B: Improving Your Skills in 12 Lead ECG Interpretation. Ems., New York, 1996.
3. Gordon C, Johnson P, Waite C, Veloso M: Algorithm and Care Pathway: Clinical Guidelines and Healthcare Processes. Lect Notes in A.I.. 121: 66-69, 1997.
4. Michie D, Spiegelhalter DJ, Taylor CC (Eds): Machine Learning & Statistical Classification: Ellis Horwood, London , 1994.

Paper from: *Data Mining III*, A Zanasi, CA Brebbia, NFF Ebecken & P Melli (Editors).
ISBN 1-85312-925-9

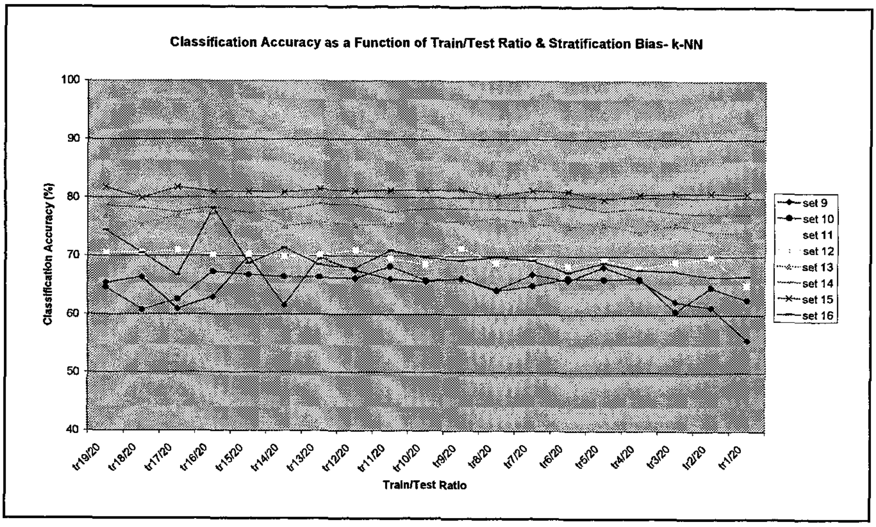


Graph 1: Classification Accuracy as a function of Train/Test Ratio with size of data set (varying the stratification bias) - C4.5

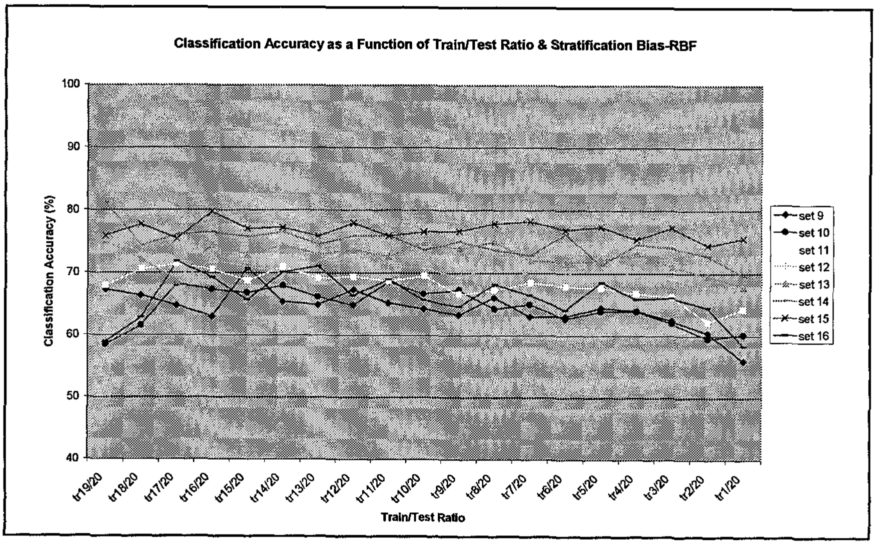


Graph 2: Classification Accuracy as a function of Train/Test Ratio with size of data set (varying the stratification bias) - CN2

Paper from: *Data Mining III*, A Zanasi, CA Brebbia, NFF Ebecken & P Melli (Editors).
ISBN 1-85312-925-9

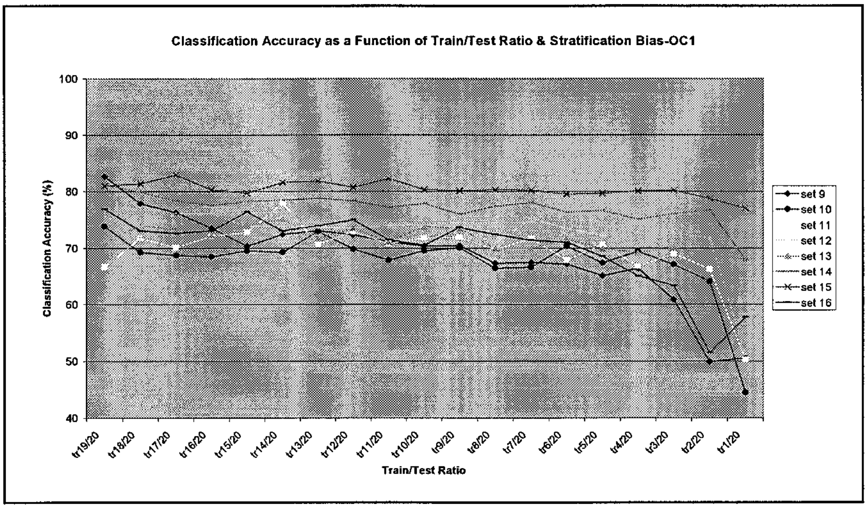


Graph 3: Classification Accuracy as a function of Train/Test Ratio with size of data set (varying the stratification bias) - KNN



Graph 4: Classification Accuracy as a function of Train/Test Ratio with size of data set (varying the stratification bias) - RBF

Paper from: *Data Mining III*, A Zanasi, CA Brebbia, NFF Ebecken & P Melli (Editors).
ISBN 1-85312-925-9



Graph 5: Classification Accuracy as a function of Train/Test Ratio with size of data set (varying the stratification bias) - OC1