Induction for Radiology Patients
(Invited Paper)

Pınar Yıldırım and Mehmet R. Tolun

Computer Engineering Department,
Çankaya University, Turkey
{pinar,tolun}@cankaya.edu.tr

Abstract. This paper represents the implementation of an inductive learning algorithm for patients of Radiology Department in Hacettepe University hospitals to discover the relationship between patient demographics information and time that patients spend during a specific radiology exam. ILA has been used for the implementation which generates rules and the results are evaluated by evaluation metrics. According to generated rules, some patients in different age groups or birthplaces may spend more time for the same radiology exam than the others.

Keywords: Medical Decision Making, Radiology Information System, Radiology Data Mining, Knowledge Extraction.

1 Introduction

Clinical information systems have accumulated large quantities of information about patients and their medical conditions. A radiology information systems(RIS) is a kind of clinical information system and provides many components of functions. In these systems, thousands of images, as well as a wealth of detailed ordering and demographic data, and a text report from the radiologist are stored and managed.

The activities in a radiology department importantly depends on workflow and consists of some multistep processes:

- Radiology examination request is booked electronically at Hospital Information System(HIS) terminal in a referring department and contains patient demographics and examination.
- The patient applies the radiology department for examination appointment
- The secretary schedules the examination, depending on the scheduled modality.
- The patient arrives for the scheduled examination, he/she is checked in at the reception
- The patient is examined
- Radiologist interprets the examination
- The exam report is generated.

The examination duration from request until report generation is a measure of efficiency of radiology department and it directly affects on departmental quality,

D. Weerasinghe (Ed.): eHealth 2008, LNICST 1, pp. 208–220, 2009.

clinical outcomes and decision making. If the duration is reduced, clinicians can receive the results and treat the patients much quicker. Therefore, short duration saves time, money, and it helps improve the quality and timeliness of patient care.

In order to improve productivity and efficiency in radiology workflow, some hidden factors affecting on long durations should be discovered in data stored in the radiology information system. In this study, the techniques of machine learning is applied to discover hidden knowledge in the Radiology information system used in Hacettepe University Hospital. ILA software is used that is a new inductive algorithm for generating a set of classification rules for a collection of training examples [1].

Data set is created according to ILA input file format and the algorithm is applied on this dataset.

1.1 Problem Definition and Algorithm Task Definition

Knowledge is one of the most important assets of healthcare organizations and it is also used by administrators to improve the quality of service [2].

Like many health centers, Radiology Department of Hacettepe University(HU) Hospitals uses information system to collect and store medical data. These data consists of patient demographics, radiological exam information and appointment details. Despite the large amount of data in this system, there is a lack of useful knowledge.

The radiology department of HU Hospitals needs to use data mining techniques and focuses on these objectives such as:

- To optimise the allocation of human and material resources
- To improve radiologicial services
- To find the relationships between patient demographics and radiology exam and turnaround time

Aim of this study is to search for hidden patterns and to discover relationship between patient demographics and time that patients spend during radiology exams.

Our hypothesis in this study is that "is patient demographics information such as age, sex and birthplace are related to the exam duration in Radiology Department?" Our study finds a answer for this question.

1.2 Inductive Inferencing Algorithms

Inductive inference is the process of taking a series of examples or observations and generating an explanation for the behaviour observed. This study uses a data-driven method attributable to Tolun et al. [1]. Inductive Leaning Algorithm, or ILA in short, generates a set of classification rules for a collection of training examples. The algorithm works in an iterative fashion, each iteration searching for a rule that covers a large number of training examples of a single class. Having found a rule, ILA removes those examples it covers from the training set by marking them and appends a rule at the end of its rule set. In other words our algorithm works on a rules per- class basis. For each class, rules are induced to separate examples in that class from examples in all the remaining classes. This produces an ordered list of rules rather than a decision tree as used by ID3 and other similar algorithms [3].

The Inductive Learning Algorithm(ILA) consists of these steps;

Step 1: Partition the table which contains m examples into n sub-tables. One table for each possible value of the class attribute (* steps 2 through 8 are repeated for each sub-table *)

Step 2: Initialize attribute combination count j as j = 1.

Step 3: For the sub-table under consideration, divide the attribute list into distinct combinations, each combination with j distinct attributes.

Step 4: For each combination of attributes, count the number of occurrences of attribute values that appear under the same combination of attributes in unmarked rows of the sub-table under consideration but at the same time that should not appear under the same combination of attributes of other sub-tables. Call the first combination with the maximum number of occurrences as max-combination.

Step 5: If max-combination = $\emptyset$, increase j by 1 and go to Step 3.

Step 6: Mark all rows of the sub-table under consideration, in which the values of max-combination appear, as classified.

Step 7: Add a rule to R whose left hand side comprise attribute names of maxcombination with their values separated by AND operator(s) and its right hand side contains the decision attribute value associated with the sub-table.

Step 8: If all rows are marked as classified, then move on to process another sub-table and go to Step 2. Otherwise(i.e., if there are still unmarked rows) go to Step 4. If no sub-tables are available, exit with the set of rules obtained so far [1].

ILA is an algorithm for extracting production rules from collection of examples. An example is described in terms of a fixed set of attributes, each of with its own set of possible values.

ILA-2 is an extension of ILA with respect to the modifications. The first modification is the ability to deal with uncertain data and the second is a greedy rule generation bias that reduces learning time at the cost of an increased number of generated rules.

1.3 Description of the ILA Algorithm with a Running Example

In describing ILA we shall make use of a simple training set. Consider the training set for disease classification given in Table 1, consisting of seven examples with three attributes and the class attribute with two possible values. The first step of the algorithm generates two sub-tables which are shown in Table 2.

Let us trace the execution of the ILA algorithm for this training set. After reading the object data, the algorithm starts by the first class(yes) and generates hypothesis in the form of descriptions as shown in Table 4. A description is a

Table 1. Disease classification training set

Example No	Age	Blood Pressure	Cigarette Use	Disease (Class)
1	25	High	Not used	yes
2	37	Normal	Seldom	no
3	37	Normal	Frequently	yes
4	53	Normal	Seldom	no
5	53	Low	Always	yes
6	53	Normal	Always	no
7	53	Low	Frequently	yes

Table 2. Sub-table 1 of The Training Set Partitioned According to Decision classes

Example no.		Age	Blood Pressure	Cigarette Use	Disease Decision
Old	New				
1	1	25	High	Not used	yes
3	2	37	Normal	Frequently	yes
5	3	53	Low	Always	yes
7	4	53	Low	Frequently	yes

Table 3. Sub-Table 2 of The Training Set Partitioned According to Decision classes

Example no.		Age	Blood Pressure	Cigarette Use	Disease Decision
Old	New				
2	1	37	Normal	Seldom	no
4	2	53	Normal	Seldom	no
6	3	53	Normal	Always	no

Table 4. The first set of description

No	Description	True Positive	False Negative
1	Age=25	1	0
2	Blood Pressure=High	1	0
3	Cigarette Use=Not used	1	0
4	Age=37	1	1
5	Blood Pressure=Normal	1	3
6	Cigarette Use=Frequently	2	0
7	Age=53	2	2
8	Blood Pressure=Low	2	0
9	Cigarette Use=Always	1	1

conjunction of attribute-value pairs; they are used to form the left hand side of rules in the rule generation step.

For the combination Age the attribute value “25” appears in Table 2 but not in Table 3, so the value of max-combination becomes “25”. Since other available attribute values “37” and “53” appear in both Table 2 and Table 3 they are not considered at this step. The occurrence of Age attribute value "25" is noted as one times and next combination is evaluated with max-combination set to "Low". For combination Blood Pressure we have "High" with an occurrence of one times and "Low" with an occurrence of two times. Continuing further with combination Cigarette Use, we have "Not used" with one occurrence and "Frequently" with two occurrences. At the end of step 4, we have Blood Pressure attribute value "Low" and Cigarette Use attribute value "Frequently" marked with maximum number of occurrences. Here either of the attribute values can be selected, because both of them can classify the same number of training examples. The algorithm always selects the first one(i.e."Low" in this case) by default, and this will make max-combination to keep its current value of "Low". Rows 3 and 4 are marked as classified in Table 2, since the value of max-combination is repeated in these two rows, the following production rule(Rule 1) is extracted:

Rule 1:
IF Blood Pressure is Low THEN the disease decision is yes.

Now, ILA algorithm repeats step 4 through step 8 on the rest of the unmarked examples in sub-table 2(i.e. rows 1 and 2). By applying these steps again we have "25" attribute value of Age, "high" attribute value of Blood Pressure, "Not used" and "Frequently" attribute values of Cigarette Use occuring once. Since the number of occurrences are the same, the algorithm applies the default rule and selects the first one considered(i.e. "25" attribute value of Age). Then the following rule (rule 2) is added to the rule set:

Rule 2:
IF Age is 25 THEN the disease decision is yes.

He first row in sub-table 1 is marked as classified and steps 4 and 8 are applied again on the remaining row(i.e. the second row). Here we have "Frequently" attribute value of Cigarette Use occuring once, so the third rule is extracted:

Rule 3:
IF Cigarette Use is Frequently THEN the disease decision is yes.

By marking the second row as classified all of the rows in sub-table 1 are now marked as classified and we proceed on to sub-table 3. The "Seldom" attribue value of Cigarette Use occurs twice in the first and second rows in sub-table 3. So,these two rows are marked as classified and Rule 4 is appended to the rule list.

Rule 4:
IF Cigarette Use is Seldom THEN the disease decision is no.

In the remaining row in sub-table 3(i.e. the third row) we have Age attribute with a value of "53" that appears also in sub-table 1. So according to the algorithm this cannot be considered. The same applies to “Normal” value of Blood Pressure and “Always” value of Cigarette Use attributes. In this case, ILA increases j by 1, and generates 2-attribue combinations, Age and Blood Pressure, Age and Cigarette Use, and Blood Pressure and Cigarette Use. The first and third combinations satisfy the conditions as they both appear in sub-table 3 but not in sub-table 2 for the sam attributes. The “53 always” value of Age and Cigarette Use combination is ignored because it already appears in sub-table 2. according to this, we can choose either the first of the third combination but the default rule allows us to select the first one. The following rule(Rule 5) is extracted and the third row is sub-table 3 is marked as classified:

Rule 5:
IF Age is 53 AND Blood Pressure is Normal THEN the decision is no.

Now, since all of the rows in sub-table 3 are marked as classified and no other sub-table is available, the algorithm terminates [1,4].

Java implementation of ILA-2 has the following features:

– user interface which makes all algorithm parameters accessible
– options saved to disk
– reading data from relational tables
– saving rules to relational tables
– possibility of running cn2 algorithm
– simple discretization support

2 Experimental Evaluation Methodology

Dataset that is analyzed by using ILA algorithm is collected from Radiology Information System used in HU Hospitals by using SQL queries. A brain MRI (Magnetic Resonance Imaging) is selected as a specific exam to create a meaningful dataset. 2844 patients who undergone a brain MRI exam were selected. The attributes of patients’ birthplace, gender and birthdate were directly collected from database. The birthplaces were categorized according to the biggest cities and regions in Turkey. Age is calculated for each patient and categorized (Table 5). The duration is selected as a class function. This value is calculated for 2844 patients and the mean value of duration is found. If the duration value of tuple is bigger than mean, it is assigned long, otherwise short (Table 6). Therefore, two classes were obtained. The dataset consists of four attributes and two classes which are short or long. There are 2021 short and 823 long instances in the dataset. Table 8. shows the attributes and categorized values. Some instances of the dataset are seen at Table 8. The attributes are patients’ birthplace, gender and birthdate. The classes in this dataset are short or long. There are 2021 short and 823 long instances. ILA accepts exactly the same input data file formats as C4.5, consisting of a name-file, a data-file, and an optional test-file. In addition to flat files, ILA can read data from relational database tables, and

Table 5. Age Categories

AGE	**CATEGORY**
$0 - 14$	CHILD
$15 - 24$	YOUNG
$25 - 64$	ADULT
$65 \leq$	SENIOR

Table 6. Duration Categories

DURATION (Mean=31 days)	**CATEGORY**
$\leq$ Mean	SHORT
$>$ Mean	LONG

Table 7. Attributes and Values

ATTRIBUTES	**VALUES**
BIRTHPLACE	ANKARA, IZMIR, ISTANBUL, AEGEAN, BLACKSEA, CENTRAL ANATOLIA, MARMARA, MEDITERRANEAN, EASTEARN ANATOLIA, SOUTHEAST ANATOLIA
GENDER	M,F
AGE	CHILD,YOUNG, ADULT, SENIOR
DURATION (Class)	SHORT, LONG

Table 8. Some Instances of The Dataset

BIRTHPLACE	**GENDER**	**AGE**	**DURATION**
BLACKSEA	M	SENIOR	LONG
AEGEAN	F	YOUNG	SHORT
ANKARA	F	CHILD	SHORT

save generated rules to relational database tables. In this study two input files is created. These are patientbrain.data and patientbrain.names that conform to ILA input data file formats.

Patientbrain.names and Patientbrain.data files are seen in Tables 9. and 10.

Table 9. The view of Patientbrain.names

SHORT,LONG	
BIRTHPLACE	: AEGEAN,ANKARA,IZMIR, ISTANBUL,BLACKSEA,CENTRALANATOLIA, MARMARA,MEDITERRANEAN, EASTEARNANATOLIA, SOUTHEASTANATOLIA
GENDER	: M,F
AGE	: CHILD,YOUNG,ADULT,SENIOR

Table 10. The view of Patientbrain.data

AEGEAN,M,CHILD,SHORT.
AEGEAN,M,CHILD,SHORT.
AEGEAN,M,CHILD,SHORT.
AEGEAN,M,CHILD,SHORT.
AEGEAN,M,CHILD,SHORT.
AEGEAN,M,CHILD,SHORT.
AEGEAN,M,CHILD,SHORT.
AEGEAN,M,CHILD,SHORT.
AEGEAN,M,CHILD,SHORT.

3 Results

After applying the ILA algorithm for patientbrain dataset, some rules are generated. The algorithm classified 2844 examples and generated 22 rules. The results are;

Number of examples 2844,
Number of classes 2,
Number of attributes 3
Number of rules 22

If GENDER =M and BIRTHPLACE =ANKARA then SHORT.
If AGE =CHILD and BIRTHPLACE =ISTANBUL then SHORT.
If AGE =YOUNG and BIRTHPLACE =AEGEAN then SHORT.
If AGE =SENIOR and BIRTHPLACE =IZMIR then SHORT.
If AGE =CHILD and BIRTHPLACE =ANKARA then SHORT.
If AGE =SENIOR and BIRTHPLACE =AEGEAN then SHORT.
If AGE =SENIOR and BIRTHPLACE =ANKARA then SHORT.
If AGE =YOUNG and BIRTHPLACE =MARMARA then SHORT.
If GENDER =M and BIRTHPLACE =IZMIR then SHORT.
If AGE =ADULT and BIRTHPLACE =IZMIR then SHORT.
If AGE =CHILD and BIRTHPLACE =IZMIR then SHORT.
If AGE =SENIOR and GENDER =F and BIRTHPLACE =ISTANBUL then SHORT.

If AGE =ADULT and GENDER =F and BIRTHPLACE =ISTANBUL then SHORT.
If AGE =CHILD and BIRTHPLACE =BLACKSEA then LONG.
If AGE =CHILD and BIRTHPLACE =CENTRALANATOLIA then LONG.
If AGE =ADULT and BIRTHPLACE =BLACKSEA then LONG.
If AGE YOUNG and BIRTHPLACE =BLACKSEA then LONG.
If AGE =ADULT and BIRTHPLACE =SOUTHEASTANATOLIA then LONG.
If AGE =YOUNG and BIRTHPLACE =SOUTHEASTANATOLIA then LONG.
If AGE =CHILD and BIRTHPLACE =MARMARA then LONG.
If AGE =CHILD and GENDER =F and BIRTHPLACE =AEGEAN then LONG.
If AGE =ADULT and GENDER =M and BIRTHPLACE =AEGEAN then LONG.

According to the results, some interesting rules are obtained from the dataset. For example, the rule, If AGE =CHILD and BIRTHPLACE =BLACKSEA then LONG, indicates that if a patient's birthplace is in the Blacksea region, the duration of the medical exam is long.

The number of rules is considered as an evaluation parameter because the main aim is to produce the minimum number of rules as possible that can classify all of the examples in the training set. The second parameter that has great significance in the evaluation process of inductive learning systems is the capability of the system to classify as much unseen examples as possible [1].

Accuracy is the other important issue for the classification applications. It is the percentage of examples in the test set that are classified correctly. There are some evaluation metrics such as TP(True Positive), FN(False Negative), FP(False Positive) and TN(True Negative) for evaluation classification applications. The true positive and True negative are correct classifications. A false positive is the class is incorrectly predicted as positive when it is in fact negative. A false negative is when the class is in fact positive.

In order to normalize the score, a simple metric is obtained from the total number of positive instances, P, and negative instances, N as

$$(TP + TN)/P + N \tag{1}$$

Considering the results, the classifier's performance should be evaluated in terms of the error rate.

Output of evaluation metrics for the patientbrain dataset is shown in Table 11 In ILA Inductive Learning algorithm, for some applications, part of the available data is reserved as a test set to evaluate the classifier produced. If there is one, the test set appears in the file filesystem.test, in exactly the same format as the data file [4]. In this study, the classifier is tested by using this feature and Table 12 shows these results.

According to Table 9, 648 instances of the dataset are used to test the classifier produced and 334 of them is classified as a 0 class, 314 of them is classified as a 1 class. Every instance in the test file is correctly classified. Therefore, there is no wrong classification. Uncovered instances are the rest of the dataset that are not used for testing.

Table 11. ILA Results

Rule No	TP	FN	Error
1	195	0	0.0
2	19	0	0.0
3	18	0	0.0
4	17	0	0.0
5	12	0	0.0
6	12	0	0.0
7	10	0	0.0
8	10	0	0.0
9	6	0	0.0
10	3	0	0.0
11	2	0	0.0
12	25	0	0.0
13	5	0	0.0
14	111	0	0.0
15	86	0	0.0
16	37	0	0.0
17	37	0	0.0
18	18	0	0.0
19	15	0	0.0
20	8	0	0.0
21	1	0	0.0
22	1	0	0.0

Table 12. Evaluation of the Classifier

Class	True Classification	Wrong Classification	Uncovered
0	334	0	1687
1	314	0	509

ILA-2 is an extended version of ILA and has additional features. These features;

- A faster pass criterion reduces the processing time and called fastILA.
- PF(Penalty Factor) is an evaluation metric utilized in ILA2.
- Different feature subset selection(FSS). With FSS, the search space requirements and the processing time will probably be reduced due to the elimination of irrelevant attribute value combinations at the very beginning of the rule extraction process [5].

As basic ILA is applied on our dataset, additional evaluation features of ILA-2 are not used.

4 Discussion

This study provides specific information obtained from administrative data of Radiology Department in HU Hospitals. Although, today many machine learning applications are performed to discovery hidden knowledge from healthcare data, these studies are usually based on radiological images and medical diagnostics. Considering this kind of researches, there is no previous published study using learning algorithm to knowledge discovery from administrative data of radiology department.

Since hospitals and clinics keep large administrative data, these data plays an important role for quality assurance of medical care and can be used to highlight practices embedded in the organization, or reveal interesting patterns among patients [6]. For example, our study reveals some hidden knowledge in radiology department. According to some rules obtained with ILA Algorithm, some patients from Southeastern Anatolia region which is undeveloped and rural area in Turkey spend more time for radiology processes in the hospital. On the other hand, other patients from big and developed cities such as Istanbul and Ankara spend less time for same exams.

The Southeastern Anatolia region in Southeast Turkey faces many of the problems that are typical of underdeveloped regions in the world. Compared with the rest of Turkey, the region has higher infant mortality, higher unemployment rates and lower literacy rates due to less access to health care and education. According to Ministry of National Education statistics, the literacy rate in the region is %68.8 [7]. The region's economy is based largely on agriculture, but productivity historically has been low. In order to solve the region' problems, Turkish Government launched The Southeastern Anatolia development Project in 1989. The project is a regional development project aiming at the full-fledged socioeconomic development [8].

The knowledge extracted with our study indicates that cultural,educational and regional factors of patients affect on the workflows in the hospitals. Radiology management should utilize our study results and define some new policies to provide time saving for patients living in rural areas.

5 Related Work

Many machine learning applications are being performed in hospital information systems to discover some hidden knowledge. In some studies, association rules are used and patient behaviors are examined to find interesting patterns among complex behaviors in the national wide health insurance data. According to results, some factors affecting on patient visits such as age, sex, rate of utilization, chronic diseases, mental disorders are discovered [9].

Data mining techniques is also used in healthcare management. Classification based data mining techniques such as Rule based, decision tree and Artificial Neural Network are frequently used for the data modeling of healthcare applications, executive Information System for Healthcare, forecasting treatment costs and demand of resources, anticipating patient's future behavior given their history and so on [9,10]. The other data modeling is used to predict whether the person is over drink-driving limit based on the data obtained from attributes for alcohol measurement such as age, sex, mass, tobacco use, height, meal(empty stomach, lunch, full) amount of alcohol and so on. Some rules are obtained [11].

Patient demographics information is generally analyzed for length of stay in the hospital and hospital related expenses. These measures are two important indicators of effective health service.In some studies, neural prediction models are used to predict the duration of stay in the hospital and hospital related expenses using demographic, environmental and hospital related factors and identify the profiles of the patients in various segments which will help in policy formulation. The data is obtained from National Sample Survey Organization(NSSO) and the duration of hospital stay and the expenditure are the two variables selected for prediction. After applications, some interesting results are discovered:

– The long duration segments have higher percentage of patients belonging to older age groups(40 years and above) where as the shorter duration segments have younger patients.
– The patients in the urban sector spend more number of days in the hospital as compared to their counter parts in the rural sector.
– The consumption of items such as alcohol, tobacco and smoking habit appear to have an impact on the stay in the hospital.
– Public hospitals appear to attract longer stay where as private hospitals attract shorter stay [12].

6 Conclusion

Healthcare domain has a big amount of data and usually many healthcare centers focus on only the implement and maintain of information systems to handle daily works. However, there is a need of knowledge that obtained from stored in data repositories in hospitals or medical centers to plan the future and to increase the productivity [10,11,12,13]. For this reason, hospital managements should consider the importance of data mining or machine applications to provide better quality healthcare services.

Despite the rich of healthcare data, many useful information is invisible in hospital and clinical information systems. Radiology Information systems are one of the big resources for knowledge discovery. In this study, relationships between patients demographics and exam duration in Radiology Department in HU Hospitals are analyzed and useful information is obtained. In the future, other hypotheses related to radiology services can be analyzed and interpreted to improve the efficiency and productivity of this department.

This paper presents a machine learning application for the patient dataset. ILA algorithm is used and evaluated to discovery hidden patterns and to search relationship between patient demographics and time that patients spend during the specific radiology exam. This algorithm extracted some hidden knowledge from this dataset by generating the rules. Considering the results, some patients in different age groups or different birthplace regions may spend more time for same radiology exam than the others.

Radiology Department of Hacettepe University hospitals should take into account this information and search new solutions to decrease the duration of exams for different patients. For example, a collaborative team should be assigned for the patients from rural areas. When the patients come to the hospital, a staff should assist them and they can easily get information about the hospital processes and the locations they have to visit. With these assisting service,the patients can be informed about hospital workflow and should not spend much time to receive healthcare services.

In conclusion, this study positively affects on the future plans and resource management of Radiology Department in HU Hospitals [14].

References

1. Tolun, M.R., Abu-Soud, S.M.: ILA: An Inductive Learning Algorithm for Rule Extraction. Expert Systems with Applications 14(3), 361–370 (1998)
2. Wasan, S.K., Bhatnagar, V., Kaur, H.: The Impact of Data Mining Techniques on Medical diagnostics. Data Science Journal 5, 119–126 (2006)
3. Quinlan, J.R.: Induction of Decision Trees. Machine Learning 1(1), 81–106 (1986)
4. Tolun, M.R.: Inductive Learning Algorithm (2007), `http://cmpe.emu.edu.tr/ila2/ilaguide.html`
5. Tolun, M.R., Sever, H., Uludag, M., Abu-Soud, S.M.: An Inductive Learning Algorithm for Knowledge Discovery, Cybernetics and Systems. International Journal, 609–628 (1999)
6. Tsechansky, M.S., Pliskin, N., Rabinowitz, G., Porath, A.: Mining Relational Patterns From Multiple Relational Tables. Decision Support Systems 27, 177–195 (1999)
7. Education Statistics, `http://www.gap.gov.tr`
8. Unver, O.: Southeastern Anatolia Development Project. IEEE Power Engineering Review, 10–12 (2002)
9. Chen, Y.C., Wu, S.C.: Exploring Out-Patient Behaviors in Claim Database: A Case Study Using Association rules. In: AMIA Symposium Proceedings (2003)
10. Nigrin, D.J., Kohane, I.S.: Data Mining by Clinicians. In: American Medical Informatics Association Symposium Proceedings (1998)
11. Kaur, H., Wasan, S.K.: Empirical Study on Applications of Data Mining Techniques in Healthcare. Journal of Computer Science 2(2), 194–200 (2006)
12. Nagadevara, V.: Application of Neural Prediction Models in Healthcare. In: Proceedings of the 2nd International conference on e-Governance ICEG 2004, pp. 139–149 (2004)
13. Kraft, M.R., Desouza, K.C., Androwich, I.: Data Mining in Healthcare Information Systems: Case Study of a Veterans Administration spinal cord Injury Population. In: Proceedings of the 36th Hawaii International Conference on System Sciences (2003)
14. Cheng, B.W., Luo, C.M., Chen, K.H.: Using Data Mining to Evaluate Patient-Oriented Medical Services for Chronic Senility. Quality&Quantity 2006 40, 1079–1087 (2006)