Intelligent Hypothermia Care System using Ant Colony Optimization for Rules Prediction

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Abstract

Intelligent Hypothermia Care System (IHCS) is an intelligence system uses set of methodologies, algorithms, architectures and processes to determine where patients in a postoperative recovery area must be sent. Hypothermia is a significant concern after surgery. This paper utilizes the classification task in data mining to propose an intelligent technique to predict where to send a patient after surgery: intensive care unit, general floor or home. To achieve this goal, this paper evaluates the performance of decision tree algorithm, exemplifying the deterministic approach, against the AntMiner algorithm, exemplifying the heuristic approach, to choose the best approach in detecting the patient's status. Results show the outperformance of the heuristic approach. The implication of this proposal will be twofold: in hypothermia treatment and in the application of ant colony optimization.

Keywords*:* Data mining, classification, decision tree, ant colony optimization, hypothermia treatment.

الخلاصة

ان انخفاض درجة حرارة جسم المريض بعد اجراء العمليات الجراحية هو مصدر قلق كبير لكثير من الاطباء بعد الجراحة. يقدم هذا البحث نظاماً ذكياً (IHCS) لمراقبة انخفاض درجة الحرارة وبناء على ذلك يتم تحديد اين سيرسل المرضى في جناح النقاهة. تتم عملية اتخاذ القرار بالاعتماد على مجموعة نتائج لفحوصات طبية حيث تمثل بيانات مدخلة للنظام (IHCS). يقوم هذا النظام بتصنيف البيانات المدخلة للتنبؤ بحالة المريض وتحديد وجهته القادمة كوحدة العناية المركزة او القسم العام داخل المستشفى او امكانية ارساله الى المنزل. ان الخوارزمية المستخدمة في هذا البحث تم اختيارها بعد اختبار بيانات المرضى على مجموعة خوازميات وهي اولا: خوارزمية شجرة القرارات, ثانيا خوارزمية النمل حيث تم استخدام قابليات النمل للبحث وايجاد اقصر مسار للطعام وتوظيفها لاستكشاف افضل القوانين للتنبؤ بحالة المريض. واخيرا تم استخدام بعض تقنيات تهيئة وتجهيز البيانات قبل معالجتها ومن ثم معالجتها بواسطة نظرية المعلومات. وبعد تقييم النتائج اتضح ان خوارزمية مستعمرة النمل تعطي افضل النتائج فتمت برمجة القوانين المستخرجة والحصول على النظام الذكي (IHCS) لمساعدة الاطباء في عملية معالجة حالات انخفاض درجة حرارة الجسم بعد العمليات الجراحية وينفرد هذا البحث لاستخدامه هذه الخوارزمية لاول مرة في هذا المجال .

الكلمات المفتاحية: تنقيب في البيانات، تصنيف، شجرة القرارات، خورازمية النمل، معالجة الهايبوثيميا.

1. Introduction

Nowadays data mining in predictive task have been widely used for health care system to help staff for making decision (Fayyad, Piatetsky-Shapiro, & Smyth, 1996). IHCS is an intelligence system to determine where to send a patient after surgery base on its hypothermia. Hypothermia is an emergency condition when patient's body loses the heat faster than it can produce heat (Inamasu & Ichikizaki, 2002) when patient's temperature passes below (35 C). It can lead to death as result of heart failure and respiratory system. Computational solutions can help in the avoidance of such dangerous after surgery.

IHCS gives important addition to the future of patient care. Such intelligent care systems are to create integration by innovation in order to create change. The proposed system used data mining algorithms to provide important tools for serving hypothermia's patients in hospitals. IHCS system will help the doctor expert in hypothermia after surgery operation for making the good decision and improve the patient safety. Also the staff with little experience will find the system useful and they can use it for assistance.

2. Literature Review

Several computational studies exist in literature to solve the problem of hypothermia. Dash and Dehuri (2013) discuss some classification techniques for data mining in field of hypothermia. Experimental techniques that utilized in the study are Naïve Bayes, ID3, J48 and fuzzy classification techniques. Results showed that the fuzzy and ID3 approaches are enough robust and more accurate that others (see Table 1).

Table 1: The prediction result using different classifier (Dash & Dehuri, 2013)

Result		
Naïve Bayes	Correctly Classified Instances	73.3333
	Incorrectly Classified Instances	26.6667
ID3	Correctly Classified Instances	88.8889
	Incorrectly Classified Instances	11.1111
J48	Correctly Classified Instances	71.1111
	Incorrectly Classified Instances	28.8889
FuzzyRoughNN	Correctly Classified Instances	88.8889
	Incorrectly Classified Instances	11.1111
FuzzyNN	Correctly Classified Instances	68.8889
	Incorrectly Classified Instances	31.1111

The downside of the work proposed by Dash et al. is that it was non experimental work. In addition, their work did not apply any of above mentioned algorithms in smart system as aid for staff for making decision.

Parpinelli et al. (Rafael Stubs Parpinelli & Benitez, 2011) proposes and algorithm called AntMiner for rules discovery in data base. AntMiner has inspired the ant behavior in nature to extract rules from dataset (Rafael S. Parpinelli, Lopes, & Freitas, 2001). The algorithm was used in some datasets which are Breast Cancer, Hepatitis and Dermatology (see Table 2). It has showed good classification performance and reduces the number of rules.

Table 2: the prediction result using AntMiner

Dataset	Predictive Accuracy	Number of Rules
Ljubljana Breast Cancer	75.13 ±6.00	5.20±0.87
Wisconsin Breast Cancer	95.47 ± 1.62	5.60±0.80
Hepatitis	88.75 ± 6.73	2.70±0.46
Dermatology	84.21 ± 6.34	6.00±0.00

3. Methodology

A systematic methodology, consists of three main processing steps, has been used to achieve the goals of this study. These are i) understanding the dataset; ii) learning using different algorithms; iii) testing the model; and iv) chose the best algorithm to develop the IHCS system, Figure 1 displays the development process.

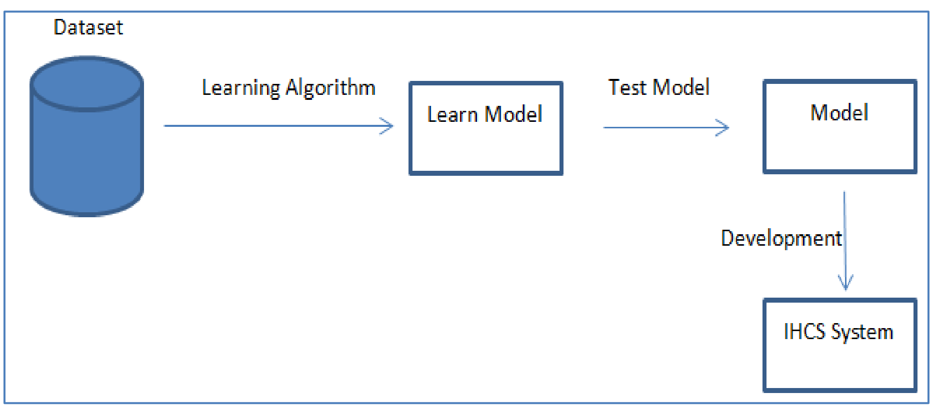

Figure 1: IHCS development structure

3.1. Hypothermia Dataset

The dataset used in this paper was collected by School of Nursing, University of Kansas and University of Missouri to determine where patients in a postoperative recovery zone must be sent after surgery operation. The data set consist of ninety records and nine features include the class attribute. The attributes are roughly patient's body measurements as follows (Brodmann Maeder et al., 2011).

i. Patient's Internal Temperature
ii. Patient's Surface Temperature
iii. Oxygen Saturation
iv. Blood Pressure
v. Stability of Surface Temperature
vi. Stability of Core Temperature
vii. Stability of Blood Pressure
viii. Comfort at Discharge
ix. The Class Attribute

Each class return's to decision whether send to emergency care unit, general hospital department or go home. IHCS developed based on human expert to overcome the Hypothermia and save time and furthermore early detection for any emergency cases.

3.2. Learning Algorithm

There are list of commonly used classification algorithms as follows:

A. Ant colony optimization

AntMiner is the main ant colony (ACO) in the field of data mining. ACO is a prominent swarm intelligence (SI) technique. SI studies the collective behavior of unsophisticated agents that interact locally through their environment it is inspired by social insects, such as ants and termites, or other animal societies, such as the bees, fish schools and bird flocks (Bonabeau, Dorigo, & Theraulaz, 1999) (see Figure 2).

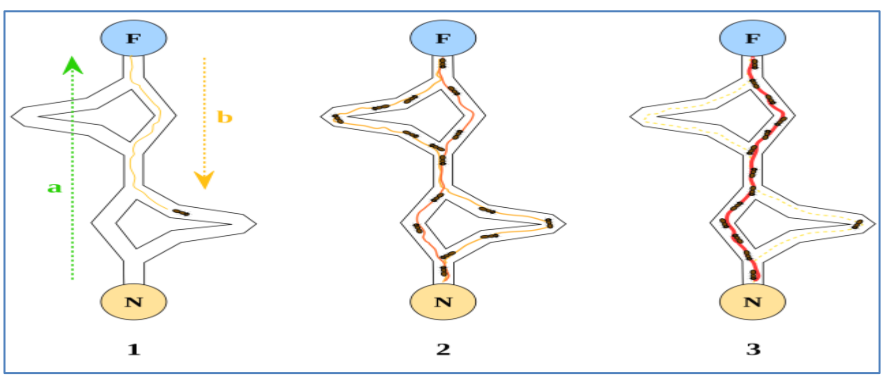

Figure 2: Ant discover shortest path between the source and the nest (Dorigo, Birattari, & Stützle, 2006)

The ability of each insect is limited but as the whole colony display hard and complex and intelligent behavior. This paper is focusing on ant colonies that exploit the nature of ants to discover the shortest path between the source and the nest. Each individual ant is a stochastic constructive procedure that incrementally builds the solution (see Figure 3) (Sagban, Ku-Mahamud, & Bakar, 2015).

procedure ACO Metaheuristic

ScheduleActivities

ConstructAntsSolutions

UpdatePheromones

DaemonActions % optional

end-ScheduleActivities

end-procedure

Figure 3: Ant colony optimization framework

B. Decision Tree using C4.5 algorithm

Decision tree classifier is widely used in medical field (Delen, Walker, & Kadam, 2005). The decision tree is a directed graph where the internal node tests an attribute, and each branch corresponds to an attribute value node and each leaf node assigns a predictive. The standard algorithm for discovering rules in decision tree is C4.5. Figure 4 depicted the functionality of this algorithm.

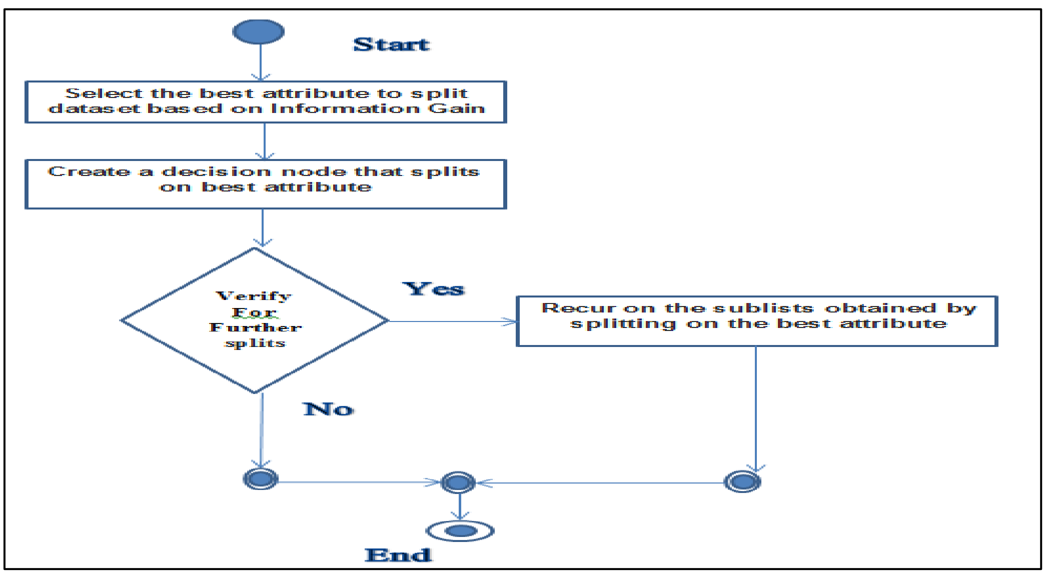

Figure 4: The procedure for C4.5 algorithm

The entropy and information gain are the criteria used for choosing the features and make the predictive for unknown class as illustrated in the following equations (Dietterich, 2000).

$$\text{Entropy}(S) = H(S) = \sum_{i=1}^{n} -p(i)\log 2\ p(i) \qquad (1)$$

$$IG(S, A) = H(S) - \sum_{v \in \text{value}(A)} |Sv|/|S|\ H(Sv) \qquad (2)$$

Where S is a sample of training examples, n is number of classes, (i) is fraction of records belongs to class, and A is an attribute.

C. Decision Tree using multiple subset

This section describes the split of the dataset to generate multiple subsets. It work based on sampling selection which is widely uses for selecting dataset. Using the subset obtained correctly classified almost using the entire dataset.

There are many sampling algorithms but we used only one which is Sampling Without Replacement (Deville & Tillé, 1998). The procedure for this technique is to remove instance from dataset when they chose for subset. Multiple dataset by decision tree technique consist three procedures which (1) split the dataset, (2) build the classification model and (3) combine the classification rules as shows in Figure 5.

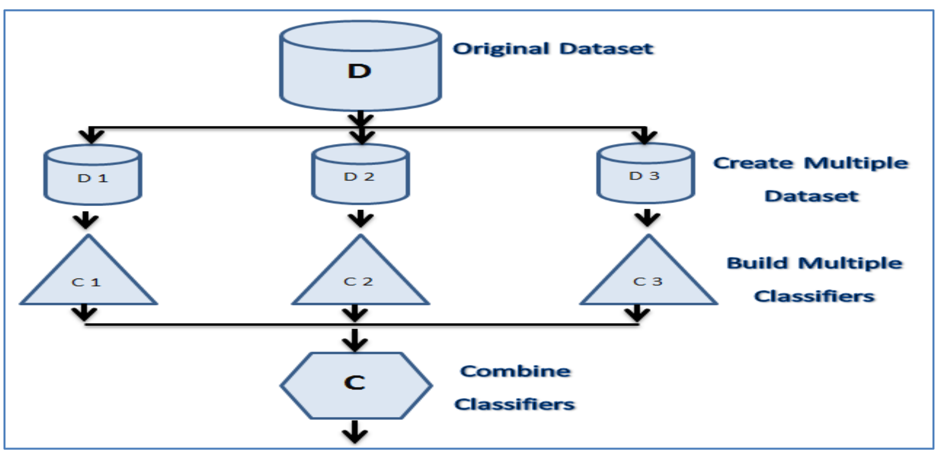

Figure 5: Learn Multiple Subset

3.3. Analyzing results

This section deals with the experimental evaluation to choose the suitable learning algorithm. The three abovementioned algorithms, i.e. ACO, DT with C4.5 and DT with multiple subsets, are used in this experimental evaluation. Results show that ACO approach is the best model for prediction. For fair evaluation, a proper cross validation test has been applied. The cross validation is randomly partitioned the original sample into subsamples. One subsample is retained as the validation data for testing the model and the remaining subsamples are used as training data. Then the cross validation is repeated k times (the Folds). The procedure of ACO start when we initialize all parameters .The parameters we used in our experiments are: The number of Cross Validation (Folds) is (10).The Number of Ants is (7). The minimum instance to discover the rule is (3). The number of uncovered cases is (5). Rules for Convergence are (10) and finally the number of Iterations (100).The next step is construct list of rules, update the pheromone, check the convergence and finally delete the used instances from the dataset. Figure 6 displays the prediction result using ACO.

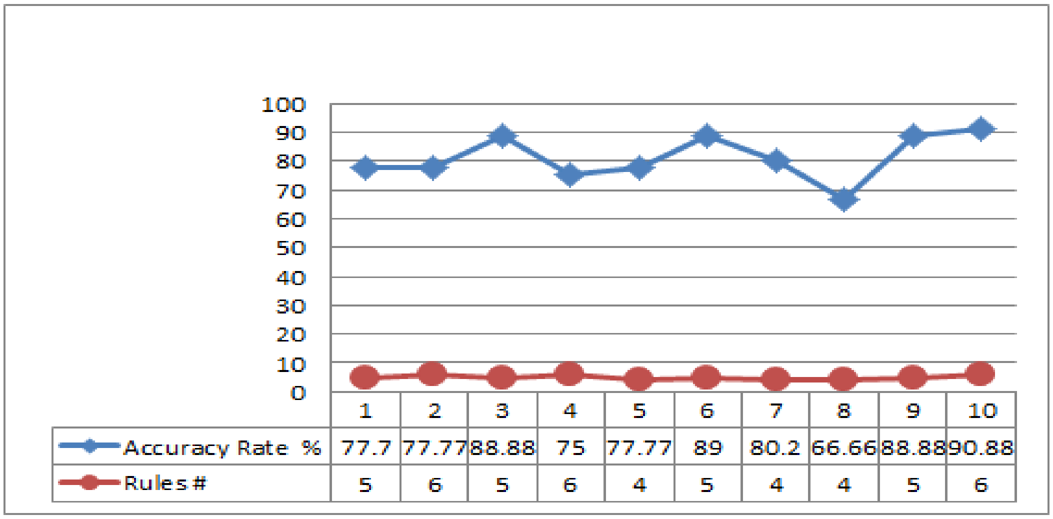

Figure 6: The prediction result using ACO

DT classifier with C4.5 standard algorithm for discovering rules used in original dataset. The main functions of such algorithms can be precisely outline. Firstly, select the best attribute to split the subset based on Equations (1) and (2). Secondly, create decision nodes based on best attributes and seek for further split. Finally, recur on the sub-lists obtained by splitting attributes and adding those nodes as children of node. The experiment and decision tree predictive result shows 70 % correctly classified instances in Table 3.

Table 3: The prediction result using DT

Stratified Cross-validation	
Correctly Classified Instances	70 %
Incorrectly Classified Instances	30 %

DT classifier with multiple subsets, each of subsets generated randomly and have different number of instances sampling has been applied. The empirical result obtained when comparing the performance of DT classifier with C4.5 algorithms for each one. The classification accuracies reported for each subset in Figure 7. The larger sampling size increases the predictively in the model.

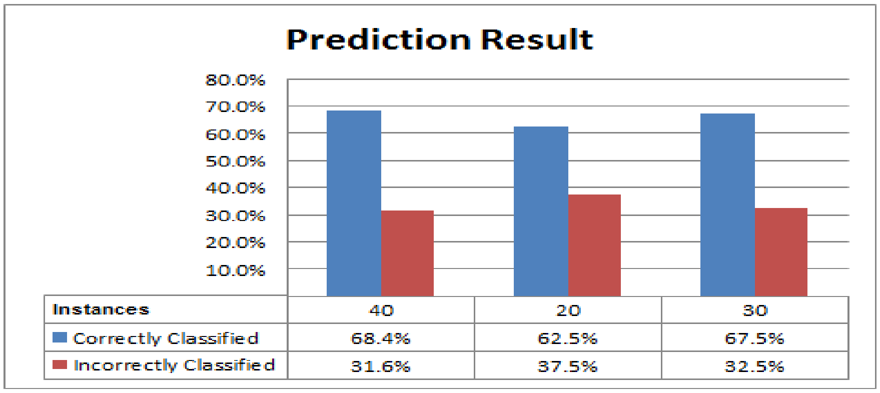

Figure 7: The Prediction Result using multiple dataset

3.4. The proposed IHCS system

In this stage, the requirement to develop the proposed system is collected. The most important step is choosing the best classifier among all in order to select the list of rules to be used in the development of IHCS system. The list of rules obtained by ACO was the best. Therefore, the list of rules collected from ACO experiments is combined. The proposed system is built using Java programming language and Eclipse Kepler. Experiments conducted on Windows 7 ultimate 32- bit Operating System, Intel (R) Core (TM) 2 Duo CPU T6400 @2.00GHZ 2.00 GHZ and RAM 3.00 GB. System process flow is based on list of rules that have been collected from ACO process. The list of rules below was generated in cross validation # 9. They are used together with other rules that have collected by best cross validation in ACO rotation.

The List of Rules:

R1: IF (Oxygen Saturation = ‘excellent’) THEN 'A'.

R2: IF (Patient's Internal Temperature = 'mid') AND (Stability of Core Temperature = 'stable') THEN 'A'.

R3: IF (Stability of Blood Pressure = 'mod-stable') THEN 'A'.

R4: IF (COMFORT = '10') THEN 'A'.

R5: IF (Stability of Surface Temperature= 'unstable') AND (Stability of Blood Pressure = 'stable') THEN 'S'.

Where A is a patient to send to general hospital department, S is a patient to send to home and I is a patient to send to emergency care unit. Once user fill-in the data and press the patients Hypothermia button, the system shows the predictive results and decide where a perspective patient should be sent. The output for the system is the decision predictive. The proposed system has feedback function as an option to save and collect more dataset instance based on expert knowledge (see Figure 8).

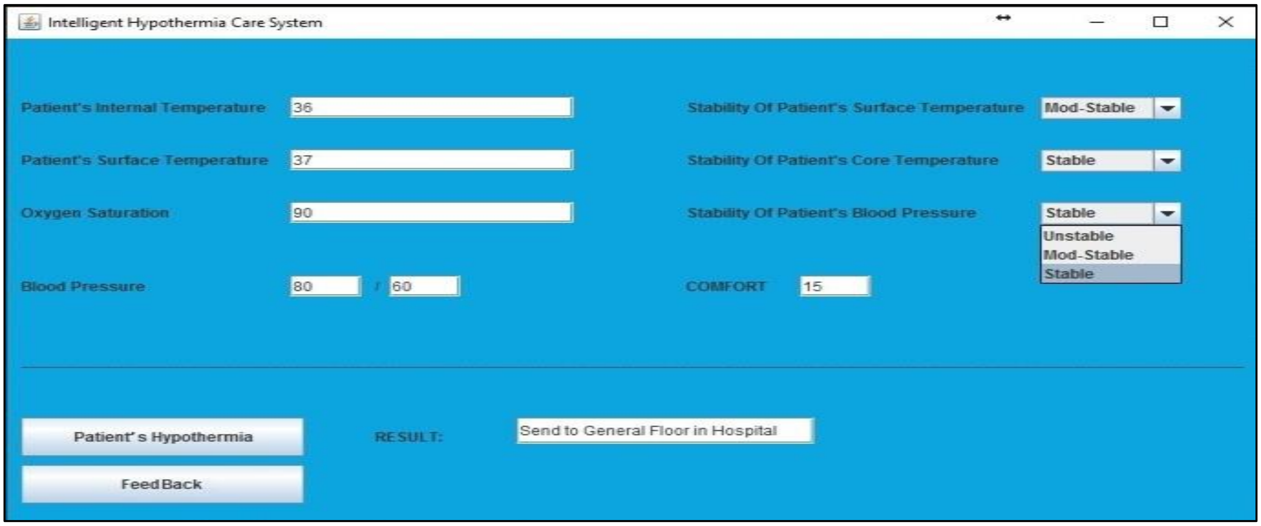

Figure 8: The system interface

4. Conclusion

The research considered as architecture for developing smart system in hypothermia care using ACO based on ant nature behavior and information theory to discover the optimal list of rules and data preprocessing to construct multiple dataset and discover the rules is applied. We have presented a data mining system in intelligent hypothermia care. We have conducted experiments on the three machine learning techniques mentioned and we compared between results. We have analyzed the result for each technique in order to determine the accuracy rate value for predictive. The result display that ACO are the best ratios among all. Furthermore, we obtained list of rules explain the diagnosis of Hypothermia according to conditions and physical body temperature. In the future we will do more research in this field using ACO to get the optimal parameters to extract rules. Moreover, our system has feedback function which responsible for collected more instances in our system data base and based on expert knowledge and it will be used in further research.

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