ANT COLONY OPTIMIZATION ON BUILDING AN ONLINE DELAYED DIAGNOSIS DETECTION SUPPORT SYSTEM FOR EMERGENCY DEPARTMENT

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Ant colony optimization (ACO) system has been applied to data mining and to develop classification rules for emergency department (ED) data sets. However, few studies focus on ACO for building a delayed diagnosis detection support system. Therefore, this paper aimed at building a high accuracy via ACO classification algorithm and back-propagation network (BPN). The research results show that ACO is with a higher accuracy rate than BPN. The output classification rules were used to build up an online medical support system that has the accuracy 80.8%.

1. Introduction

Medical error is the 8th leading cause of death of USA and more than 44,000 people's death each year (Institute of Medicine investigation report). Delayed diagnosis, one common case of medical errors, is exactly one important subject of debate in medical field. Delayed diagnosis happened in many preclinical cases including breast cancer, tuberculosis [1], internal bleeding, and infection [2]. Most doctors determine if the patient is cured by their personal experience. Unfortunately, there are not many precise rules for consultation. Even though the instruments are updating and convenient, some doctors' dependence on those instruments for patient treatment makes them ignoring the clinical alertness, and causes delayed diagnosis. In this situation, not only the patient loses their protection but medical dispute also happens, especially in the emergency room. Economically, delayed diagnosis causes the waste on medical resources and even society resources.

Artificial intelligence has been used on medical diagnosis [3] (e.g. neural network [4] and SVM [5]). In general, medical problems are divided into small, simpler parts, and can be analyzed as sub-problems by using decision tree or classification rules. Similarly, to prevent delayed diagnosis is not an intuitive estimation; on the other hand, it is inextricable that lots of factors and attributes needed to be considered. Shen [6] applied affinity set on the key attributes of delayed diagnosis problem. In conclusion, artificial intelligence on medical field is being taken more notice on.

In artificial intelligence techniques, ant colony optimization (ACO) algorithm that was proposed by Dorigo [7-9] is a high-accuracy algorithm in bionic search, which has been applied to various types of real world classification problems. One feature of ACO is that the classification rules can be learned and developed, and that feature can be applied to build up a diagnosis system; therefore, ACO was applied to many fields including data mining, data clustering [10, 11], and classification [12-16]. Other advantages of ACO are the ability of the fast convergence to the optimal solution and high accuracy [8, 9]. Therefore, this paper aimed at building a high accuracy delayed diagnosis detection support system via ACO classification algorithm and then the results were compared to back-propagation network (BPN).

2. ACO classification system for building delayed diagnosis detection system

ACO classification rules have been applied to images [15], web pages [14, 17], patterns, diagnosis [18], experts finding [19], etc. With high-accuracy, ACO classification rules are capable to be applied to build up a diagnosis detection support system (i.e. decision support or expert system). As well known, a classification rule consists of two parts (Figure 1). According to this form, a rule in ACO algorithm can be designed as a solution path through at least one of the condition nodes to exact one class node as shown in Fig.2. Moreover, the same attribute appears only once in a rule path.

Figure 1.
Two parts of a classification rule.

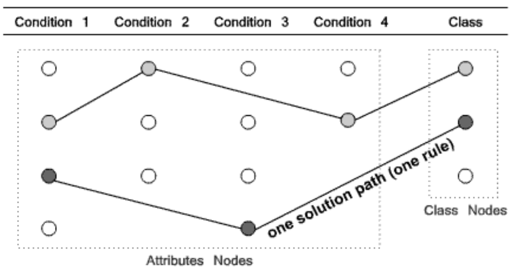

Figure 2. Each solution path denotes a classification rule

Hence, the ACO model can be used to determine some better solution paths (better classification rules). The ants construct paths by selecting condition-nodes and class-nodes [16, 20]. Based on Dorigo's theory [9], initial choice is random, classification rule set is empty, and every path has equal pheromone intensity as in Eq. (1) with *a* (total number of attributes) and *b* (number of values in the domain of attribute *i*). Condition-nodes are randomly chosen to add into current rule with possibility as Eq. (2) where $i \in$ {attributes not yet used by the ant}.

$$\tau_{ij}(t=0) = \frac{1}{\sum_{i=1}^{a} b_i} \quad (1) \qquad p_{ij}(t) = \frac{\tau_{ij}(t)\eta_{ij}}{\sum_{i}^{a}\sum_{j}^{b_i}\tau_{ij}(t)\eta_{ij}} \quad (2)$$

After the ant traversing the path (if all condition attributes are involved or adding any additional sub-path cannot cover any more cases), the ant chooses a class-node. Hence, the path becomes a rule with quality Eq. (3). (TP: true positive; TN: true negative; FP: false positive; FN: false negative) Afterward the rule has to be pruned by removing some nodes. This removal makes the maximum increasing of the quality of the rule. However, after pruning the rule, the rule may be assigned a different predicted class to fit a better quality. As each ant construct a rule, one rule of highest quality is remained to be a classification rule, and others are abandoned. Then, cases match to this classification rule are removed, and other cases are reformed into a new training set. At the time, the pheromone intensity of each condition-nodes covered in the classification rule is updated as follows. In Eq. (4), $\rho \in [0,1]$ is the evaporation rate of pheromone; on the other hand, $(1-\rho)$ means the deposited rate of pheromone.

$$Q = \left(\frac{TP}{TP+FN}\right) * \left(\frac{TN}{FP+TN}\right) \quad (3) \qquad \tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \tau_{ij}(t) * Q \quad (4)$$

Other condition-nodes not covered in the classification rule are updated as Eq. (5). The progress repeats until the number of cases in the training set is not greater than the maximum number of uncovered cases that is given as an end-condition.

$$\tau_{ij}(t+1) = \frac{\tau_{ij}(t)}{\sum_{i}^{a}\sum_{j}^{b_i}\tau_{ij}(t)}, \forall i, j \quad (5)$$

3. Research design of ACO classification system

3.1. *Research procedure*

This paper aimed to construct the delayed diagnosis detection support system. First of all is to present the delayed diagnosis data set, and then to set ACO parameters to analyze the data set. After the classification rules come out, we pick a rule set to build up our support system.

3.2. *Attributes of delayed diagnosis dataset*

In the diagnosis dataset obtained from emergency department (ED) in hospital database, we first removed the fields about personal information for protecting the patients' privacy. After that, the dataset consists of seven attributes: age, injury triage, consciousness, breath, blood pressure, pulse, and body temperature. Doctor's diagnosis is the target/output class. Those attributes are easily, quickly to measure by the instruments and explicit routines to classify patients' condition. The attributes are organized and recoded into ordinal numbers as Table 1.

Table 1. Attributes of delayed diagnosis dataset and the descriptive statistics

Attribute	Range	Code	People	Percent
Age	Younger than 30 years old	1	277	31.5%
	30 - 60 years old	2	372	42.3%
	Older then 60 years old	3	230	26.2%
Injury Triage	First Class	1	538	61.2%
	Second Class	2	300	34.1%
	Third Class	3	41	04.7%
Consciousness	Clear	1	573	65.2%
	To Call	2	95	10.8%
	To Pain	3	79	9.0%
	Coma	4	132	15.0%
Breath	10 to 24/min	1	771	87.7%
	Other	2	108	12.2%
Blood pressure	90 - 140mmHg	1	252	28.6%
	Other	2	627	71.3%
Pulse	60 - 100/min	1	347	39.4%
	Other	2	532	60.5%
Body temperature	35.5℃ - 37.5℃	1	523	59.4%
	Other	2	356	40.5%
Doctor's diagnosis	Delayed diagnosis occurred	1	743	84.5%
	Delayed diagnosis did not occur	2	136	15.4%

3.3. *ACO parameter settings*

This study used Ant Miner, an ACO software, to construct classification rules. After pretest of folds and number of ants, the parameter settings are shown as Table 2 with totally higher accuracy.

Table 2. Ant Miner parameter settings

User-defined Parameters	Value	User-defined Parameters	Value
Folds	10	Max. Uncovered Cases	10
Number of Ants	10	Rules for Convergence	10
Min. Cases per Rule	5	Number of Iterations	100

4. Data Analysis

4.1. *ACO classification rules*

A rule set is chosen with self-tested accuracy rate 84.2% on the training dataset and 89.88% on the test dataset. A confusion matrix is shown as Table 3.

Table 3. Confusion matrix of ACO classification rules

		Actual value	
		Delayed diagnosis Occurred	Delayed diagnosis Did not occur
System prediction	Occur	TP = 698	FP = 123
	Not occur	FN = 45	TN = 13
		Total accuracy: 80.8% The real possibility of diagnosis delay: 5.1% TPF (Sensitivity) = 93.9% TNF (Specificity) = 9.6%	

By the classification rule set, 80.8% cases among the patients are correctly predictable. Most important, the possibility of delayed diagnosis is lower from original 84.52% to 5.1%. 698 from the 743 delayed diagnosis cases were detected; it means that almost 94% among the patients who has to face the situation of delayed diagnosis now will be secure. Not only the patients can have higher protection, the hospital can also make effective use of medical resources. Then, the accuracy with back propagation neural network (BPN) method is checked afterward. We run the dataset by neural network software Super PCNeuron. The parameter settings are listed in Table 4. Shown as Table 5, it is obvious that ACO has much higher accuracy in the delayed diagnosis cases.

Table 4. Parameter settings of BPN

Parameters	**Value**	**Parameters**	**Value**
Neurons in the 1st hidden layer	7	Learning rate minimum bound	0.10
Neurons in the 2nd hidden layer	2	Momentum factor initial value	0.50
Training examples	586	Momentum factor reducing rate	0.99
Test examples	293	Momentum factor minimum bound	0.10
Learning rate initial value	1.00	Training cycles	10000
Learning rate reducing rate	0.99		

Table 5. Accuracy comparison of ACO and BPN

	TP	**TN**	**FP**	**FN**	**Total Accuracy**
ACO	698	13	123	45	80.8%
BPN	651	11	125	92	75.3%

5. Conclusions and Economical Implications

By using ACO rules our system that has 80.8% accuracy is very helpful for hospitals to prevent delayed diagnosis from happening in time, it also has the feature that can be easily operated with a user-friendly interface for doctors in ED. Our online delayed diagnosis detection support system that embedded ACO classification rules is developed in PHP language, which is easily installed and managed for hospitals on a web server. The interface consists of 3 parts: banner for the system label, attributes select form with a sanding button labeled "Analyze", and an output form (shows out after sanding selected values).

The most important purpose of this delayed diagnosis detection support system is to protect patients from diagnosis errors. In the economical meaning, our system is able to help hospitals actually cure patients as soon as possible with limited and valuable financial and human resources. If not, the more time of treatment is delayed, the more medical resources are wasted. Not only patients' money and hospitals' medical resources, even the whole society resources, like health insurance and care workers' manpower, will be wasted.

Therefore, to apply the support system in the emergency department is an early alarm to prevent medical dispute, the waste of medical resources, and reduce health insurance expenditure. Doctors or even nurses can easily use the system (by several clicks on the web system) to check the possibility that delayed diagnosis happens after diagnosing each patient. Rather than paying more financial and human resources to "re-cure" those patients, our system remind the hospital to wear a red tag on high risk group, and tracking those patients' status and estimation after the patient was transferred from emergency room to normal ward. Furthermore, according to the system hospitals can arrange subsequent visit after the patients are discharged from hospitals, or at least warn the patients and their families to pay more attention if some biliousness occurs.

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