Comparison of Alternative knowledge Acquisition Methods for Allergic Rhinitis

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ABSTRACTS

This paper compared four knowledge acquisition methods (namely, neural network, case-based reasoning, discriminant analysis, and covariance structure modeling) for allergic rhinitis. The data were collected from 444 patients with suspected allergic rhinitis who visited the Otorlaryngology Deduring 1991-1993. Among four knowledge acquisition methods, the discriminant model had the best overall diagnostic capability (78%) and the neural network had slightly lower rate (76%). This may be explained by the fact that neural network is essentially non-linear discriminant model. The discriminant model was also most accurate in predicting allergic rhinitis (88%). On the other hand, the CSM had the lowest overall accuracy rate (44%) perhaps due to smaller input data set. However, it was most accurate in predicting non-allergic rhinitis (82%).

Key Words : allergic rhinitis, neural network, case-based reasoning, covariance structure modeling, discriminant analysis.

I. INTRODUCTION

Allergic rhinitis has been ranked as the sixth most prevalent chronic condition in the United States, outranking heart disease (Smith, 1988). In England, morbidity of allergic rhinitis had increased twofold from 1974 and 1982

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(Fleming, 1987), and its prevalence rate ranged from 10 to 15 percent in 1987 perhaps due to environmental changes (Trigg, 1991). According to the Japan National Health Insurance records, morbidity of allergic rhinitis had increased threefold during the 10 year period from 1981 to 1990 in Japan (Miyao et al, 1993). While exact prevalence of allergic rhinitis is not known in Korea, there are many evidences that its prevalence is also increasing as air pollution has become more serious problem and foreign plants are being imported in recent years. Allergic rhinitis implies the existence of a hypersensitivity response to foreign allergens mediated by IgE antibodies. The common allergens include pollens of grasses, weeds, and trees ; animal danders; house-dust mites; insects; mold spores ; and foods. The hallmark of allergic rhinitis is the temporal correlation of nasal symptoms with exposure to allergens.

A careful clinical history and physical examination are basic in the diagnosis of nasal allergy. There are several complementary tests which have proved useful. The most widely used ones are skin tests and specific IgE (mainly RAST). However, none of these is completely reliable and often the diagnosis is based exclusively on clinical finding (Romero and Scadding, 1992). The treatment of a patient with allergic rhinitis is also problematic and has largely been depend on experience. A major difficulty in proposing a logical approach to therapy is the limited information available on the natural history of allergic rhinitis and its prognosis without treatment (Naclerio, 1991).

Many studies on allergic rhinitis have also been carried out in Korea. Most of these studies were related to patient characteristics such as symptoms (Kim et al. 1980; Moon et al. 1983), aggravating factors (Song et al. 1982), past and family history (Song et al. 1982 ; Oh et al. 1989), skin test (Kim et al. 1990 ; Yoo et al. 1991), and physical examination (Min et al. 1983). However, most of such studies on allergic rhinitis have focused on describing individual patient characteristics and risk factors separately using descriptive statistics (e.g. mean, percentage), and therefore relative importance of these factors could not be compared together and their statistical significance could not be established.

As new medical technology and knowledge are introduced everyday, there is a particular need for a computer system that will help doctors make timely decisions on diagnosis and treatment with new, up-to-date knowledge. Shortliffe (1987) has defined medical decision support systems (MDSS) as those systems which deal with clinical data or medical knowledge and which perform one or more of the following tasks : serve as a tool for information management ; help doctors to focus attention or give advice in the form of a patient-specific consultation. Most of these systems use an artificial intelligent (AI) approach based on decision rules, statistical models, and symbols to acquire and represent medical knowledge. Since they are primarily designed to support the decision-making of doctors by providing expert (or specialized) knowledge rather than routine operational information, they are often called medical expert systems.

The first such MDSS was MYCIN which was developed to assist doctors in prescribing antibiotics (1976). Since then, many expert systems have been applied to various medical fields such as : Digitalis therapy advisor (Gorry et al. 1978) ; ONCOCIN for Hodgkin's disease (Shortliffe, 1981); INTERNIST for internal medicine(Miller et al. 1982) ; QMR for general medical refernces (Miller et al. 1986) and QMR with speech recognition capability (Shiffman et al. 1991). In Korea, medical diagnosis systems were developed for hearing loss (Chae et al. 1989) and for nasal allergy (Jang, 1990; Chae et al. 1992a).

Since the beginning of expert systems techonology, however, knowledge acquisition has long been considered to be the major constraint in the development of expert systems in the medical field. The majority of incidences of reported knowledge acquisition problems involved problems with the quality of knowledge elicited. Much of this was because doctors (human experts) tended to communicate shallow knowledge rather than the required deep knowledge structure or they found it difficult to describe procedures and routines. In addition, knowledge acquisition from a standard clinical examination is also troublesome because patients' responses are very subjective and they may contradict themselves, sometimes repeatly, when describing symptoms (Mouradian, 1990).

To solve some of these problems, there have been several attempts to acquire knowledge base directly from the medical database (Moore, 1988). Neural network is one of such attempts. Neural network is considered to be one kind of the non-linear discriminant function. Information is represented in a neural network in that pattern of interconnection strengths among the processing elements. There are few applications for neural networks in the medical field including the system for diagnosis and treatment of Acute Sacrophagal disease (Gallant, 1988).

While the neural network approach offers useful tool for knowledge acquisition, unlike human experts, they solve problems by reasoning from principles. That is, it explains their reasoning by reporting the string of deductions that led from the input data to the conclusion. Medical doctors, however, solve new problems by analogy with old cases and expain reasons in terms of prior experience. Computer systems that solve by analogy with old ones are called case-based reasoning (CBR) systems (Rich et al. 1991). A CBR system draw its power from a large case library, rather than from a set of principles.

Another knowledge acquisition method is the statistical method called covariance structure modeling (CSM) which obtains a knowledge by analyzing the structural relationship among patient characteristics, diagnosis, treatment method, and its result for allergic rhinitis patients. During the last decade, CSM has emerged as a powerful technique to investigate structural relationships among variables and to test theories. While CSM has never been used in analyzing allergic data, it has been widely used in the fields such as Education (Alwin and Arland, 1984), Psychology (Lee, 1987), Demography (Beckman et al, 1983), and Epidemiology (Lee, 1993; Kim, 1993).

The purpose of this study was compare four knowledge acquisition methods (namely, neural network, CBR, discriminant analysis, and CSM) for allergic rhinitis. This analysis can help develop the MDSS for the treatment of allergic rhinitis and may provide additional therapeutic information for allergy patients.

II. MATERIAL AND METHOD

1. Subjects

The study subjects were 444 patients who visited the Otolaryngology Department of Inje University Paik Hospital with allergic symptoms from September 1 1991 to August 31 1993. Back-propagation neural network model, CBR, and discriminant model were developed using 394 cases for training and 50 cases for testing. However, only 274 cases with complete information about patient characteristics, physical examination, laboratory test, diagnosis, treatment methods, and results were used in the CSM.

2. Methods

1) Neural Network

In this study, back-propagation with sigmoid transfer function, which allows a variable number of hidden layers within the network, was selected using allergic status as output node (i.e. allergic rhinitis=1, non-allergic rhinitis=0) and 98 patient characteristics as input nodes. A number of hidden nodes, a number of traingings, and parameter values were determined from the previous study (Chae et al. 1992b) based on a series of sensitivity analysis using a correct rate as a performance measure. The correct rate refers to a percentage of the simulated cases from the test data set whose absolute differences from the actual diagnosis given by doctor were less than 0.125.

From the previous study, a hidden layer with 6 nodes produced the best results. Surprisingly, the correct rate did not monotonically improve as the number of trainings (or learnings) increase. In fact, 30,000 trainings produced better correct rate than 50,000 trainings. When a learning coefficient, which determines a delta weight, was varied from 0.1 to 0.9 while alpha was fixed at 0.5, learning coefficient of 0.6 produced the best correct rate. Similarly, when alpha was varied from 0.1 to 0.9 while mue was fixed at 0.5, alpha value of 0.1 produced the best correct rate.

This study examined the relative predictive importance of the input nodes by partitioning the sum of effects on the output layer. These are represented by the "Shares" using the following equation (Garson, 1991) :

$$\frac{\sum_{i}^{n_h} \left(\frac{Iv_j}{\sum_{k}^{n_h} IV_j} O_j \right)}{\sum_{i}^{n_v} \left(\sum_{j}^{n_h} \left(\frac{Iv_j}{\sum_{k}^{n_v} Iv_j} O_j \right) \right)}$$

For each j of n_h hidden nodes, sum the product formed by multiplying the input-to-hidden connection weight of the input node I of variable v for hidden node j times the connection weight of output node o for hidden node j ; then divide by the sum of such quantities for all variables. The result is the percentage of all output weights attributable to the given independent variable and thus represents the relative importance of the independent variable. In short, this process partitions the hidden-to-output connection weights of each hidden node into components associated with each input node shares.

For the prevention as well as treatment of Allergy, doctors need to know which of the inputs has the most effect on the output. This study also identified such sensitive inputs to the output using the "Explain" function of the Neuralworks Professional II/Plus package. "Explain" allows you dither the input values by plus or minus a percentage of the input values, and then view how much the outputs changed as a percentage of the input change. The input which has the most effect on the output needs a great deal of attention by the doctor.

2) Case-based Reasoning

A CBR system draws its predicting power from a large case library, and therefore, to be successful, cases should be well organized in memory, only relevant cases should be retrieved from memory, and previous cases be effectively adapted to new problem (Rich et al. 1991). In this study, a case was constructed to represent an allergic rhinitis condition with features for describing the symptoms associated with a condition as well as features for treatment using the ART-IM (Inference Corp, 1991). ART-IM offers a mean of implementing CBR systems by searching a collection of stored cases, which are represented as schemas, to find and retrieve the cases which most closely resemble (match) a newly presented case. The CBR system was developed based on the sequence of four events : building a case base, adding features to a case base, adding cases to a case base, and matching cases.

A stored case matches a presented case when it contains similar features. The degree of match depends on the degree of similarity. With the ART-IM, the best matching cases and their scores were retrieved. Scores ranged from 1.0 for cases that exactly match to -1.0 for cases that completely mismatch. A case's score was computed based on how closely the features of the presented-case schema match the features of the stored-case.

3) Discriminant analysis

(1) Determination of common factors on patient characteristics

Patient characteristics analyzed in this study were : 42 questionnaire items, physical examination, and laboratory test. Since a number of variables were too many for the statistical analysis, these variables were combined into smaller number of common factors using factor analysis (Chae et al. 1989). As seen in Table 1, patient characteristics were divided into 7 homogeneous categories first and then common factors were derived from each category using the factor analysis.

(2) Determination of factors affecting the diagnosis and treatment results

The factor scores for the common factors obtained from step 1 were used as independent variables to determine which factors were important in predicting diagnosis and treatment results in the discriminant analysis. Two types of dependent variables were used in the analysis : differential diagnosis (1=allergic rhinitis, 0=non-allergic rhinitis) and treatment result (1=improved, 0=not improved). Non-allergic rhinitis was comprised of three diagnostic categories : probable allergic rhinitis, non-allergic rhinitis, and sinusitis.

4) Covariance structure model (CSM)

The significant factors on patient characteristics identified from the discriminant analysis were used as independent variables for determining the structural relationship among the patient characteristics, diagnosis, and the treatment results based on the covariance structure modeling (CSM). The relationship between patient characteristic and treatment methods were determined by clinical judgement. Variables were recategorized for the analysis as follows : treatment (1=surgery, 0=drug therapy) and results (0.25=no change, 0.5=little improved, 0.75 =much improved, 1.0=cured). Since measurement of these variables were mixture of ratio variables, ordinary variables, and nominal variables, ordinary path analysis could not be used. The CSM used in this study not only can handle all these variables, but has a capability of handling measurement error for each variable.

CSM is well known by other names such simultaneus equation modeling, linear stuctural relations (LISREL) modeling, or causal modeling. All of these different names represent techniques concerned with hypothesizing, testing, modifying, and cross-validating models to analyze empirically observed covariance data (Lee, 1987). Historically, CSM is an outgrowth of path analysis in biometrics and factor anlysis in psycometrics.

CSM generally consists of two submodels : measurement model and structural model. CSM is a general method of modeling and testing the relationships among the measured variables (MVs) and latent variables (LVs). MV is variable that is directly observed and measured, whereas latent variable (LV) is a hypothetical construct that is not directly measurable, but is approximated by using valid and reliable MVs as indicators. Given the sample covariance data of MVs, one can estimate the unknown parameters and evaluate the goodness of fit of the model. A brief of the mathematical framework of CSM is presented here to define the equations.

Structural equation model : $=\eta=B\eta+\Gamma\xi+\zeta$

Measurement model : $Y=\lambda_y\eta+\varepsilon$, $X=\lambda_x\xi+\delta$

where X : independent MV (patient characteristics)

Y : dependent MV (Y_1=diagnosis, Y_2=treatment method, Y_3=result)

ξ : : independent LV, η : dependent LV

δ : error of independent MV, ε : error of dependent LV

ζ : equation error of residual

λ_x : factor loading of X on ξ, λ_y : factor loading of Y on η

Γ : path coefficient matrix between independent LV and dependent LV

(γ : indivisual path coefficient)

B : path coefficient matrix between dependent LVs

(β : individual path coefficient)

The proposed model was evaluated in terms of the overall fit. Multiple fit indexes were adopted due to the absence of an accepted single best index at present. They are : x^2 (chi-square), x^2/df (degrees of freedom), Goodness-of-fit Index (GFI), Adjusted Goodness-of-fit Index (AGFI), and Critical N (CN). x^2 tests the null hypothesis that there is no difference between the model-implied covariance matrix (or the proposed model) and the observed covariance matrix. x^2 test is known to be sensitive to large samples and to departure from multivariate normality of the observed variables (Bollen, 1989; Joreskog and Sorbom, 1989). Both occasions inflate an obtained x^2 value and might lead to the rejection of an acceptable model. Being aware of these problems of x^2 test, x^2df was suggested as a measure of a goodness-of-fit instead and small values of the ratio (less than 2) indicate a good fit (McIver, 1981). GFI measures "the relative amount of variances and covariances in the observed covariance matrix jointly accounted for by the model" and AGFI adjusts for the degrees of freedom (Joreskog and Sorbom, 1984). Both indexes range between 0 and 1. Finally, CN is a number of samples that must reach in order to accept the fit of a given model. Hoelter (1983) suggested that CN values exceeding 200 as an indication of an acceptable fit.

III. RESULTS

1. Neural network

Ten most important "Share"s for the neural network based on these parameters were presented in Table 1. The most important input node influencing diagnosis was symptom (sneezing). Using the "Explain" function of the Neuralworks, the five most sensitive input nodes for determining both non-allergic rhinitis were determined as seen in Table 2. They were : four input nodes representing negative skin tests and positive symptom (rhinorrhea). Table 6 shows the comparison of diagnostic accuracy among neural network, case-based reasoning, discriminant analysis, and CSM. Compared with the actual diagnosis made by the doctor, diagnostic capabilities for the neural network were : 72% for allergic rhinitis, 80% for non-allergic rhinitis, and 76% for the total.

Table 1. Ten most important "Share"s obtained from the neural network

(Unit : percentage)

Variable	Share
Symptom (sneezing)	1.49
Past history (rash)	1.43
Severity of symptom (sneezing)	1.32
Skin test (animal)	1.28
Family history	1.26
Daily predominance (all day)	1.25
Aggravating factor (cold air)	1.24
Septal deviation	1.23
Stuffy nose while sneezing	1.21
Runny nose (watery)	1.21

Table 2. Changes in outputs as 5 percentage of the input change

Non-allergic rhinitis			Allergic rhinitis		
Input node	Input value	% change in output	Input node	Input value	% change in output
95	0	21.0	95	0	22.7
97	0	19.6	97	0	20.5
94	0	16.7	94	0	17.9
89	0	15.9	89	0	17.3
7	1	15.3	7	1	15.1

Input node : 7=sysymptom (rhinorrhea)
89= skin test (tree)
94= skin test (D.P.)
95= skin test (house dust)
97= skin test (D.F.)

2. Case-based Reasoning

Table 6 shows the diagnostic capability of the CBR approaches when they were compared with the actual diagnosis made by the doctor. Overall diagnostic capabilities of the CBR were lower than those of the neural network. They were : 48% for allergic rhinitis, 76% for non-allergic rhinitis, and 62% for the total.

3. Discriminant analysis

1) Determination of common factors from patient characteristics

As seen in Table 3, several common factors were derieved from each of 7 categories of patient charcteristics : 6 factors from the symptom category, 4 factors from the severity category, 3 factors from the time factor category, 2 factors from the aggravating factor category, 5 factors from the family and past history category, 6 factors from the physical examination category, and 4 factors from the test category.

2) Determination of factors affecting the diagnosis and the treatment results

The significant factors affecting the diagnosis were selected from the discriminant analysis using the factors obtained from the previous step. As seen in Table 3, the following factors were selected from each category of patient characteristics : itching nose and sneezing from the symptom category, daily predominance from the time factor category, discharge and presence of polyps from the physical examination category, and all four factors from the laboratory test categories. The factors affecting the treatment results were : headache and general symptom from the symptom category, daily predominance from the time factor category, working condition (cold

Table 3. Results of factor analysis on patient characteristics

Category of Patient char.	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Symptom	Runny nose Itching eye (2.3,16.3)	Headache[a] general symptom (1.6,281.1)	Itching nose[a] Sneezing (1.1,36.2)	Rhinorrhea (1.1,43.9)	Nasal obstruction (1.1,51.5)	Hyposmia (1.0,58.6)
Severity	Nasal obstruction (2.2,21.7)	Duration of symptom during day (1.3,34.3)	Frequency of sneezing during year[a,b] (1.1,45.6)	Duration of symptom (1.0,56.0)		
Time factor	Seasonal predominance (1.6,20.3)	Daily predominance (1.4,37.9)	sleep (1.1,52.0)	Before		
Aggravating factor	House(dusting, smoking) (1.9,26.7)	Work place (cold air)[b] (1.2,44.0)				
History	Past history (Asthma) (1.4,14.3)	Past history (nasal surgery urticaria,etc) (1.3,27.2)	Family history (1.2,27.2)	Atopy (1.1,49.8)	Medication[b] (antibiotics) (1.0,60.0)	
Physical examination	Mucosal color (Pink,Bluish) (2.4,21.4)	Septal[a] deviation (1.6,35.9)	Presence of[a] nasal polyps (1.3,47.8)	Swelling (1.2,58.3)	Middle meatal block (1.1,67.9)	Mucosal color (Pale) (1.0,77.2)
Test	Skin test[a] (Mite,animal) (3.5,28.9)	Skin test[a,b] (Mold,tree) (2.3,48.4)	Laboratory[a] test(IgE, Eosinophilia) (1.3,59.6)	Skin test[a] (Mugwort) (1.1,68.4)		

Figures in parenthesis are eigen value and cummultive variance of each factor
a : Factors significantly affecting the diagnosis
b : Factors significantly affecting the treatment result

air, etc.) from the aggravating factor category, medication from the history category, skin test (mold, etc.) from the test category.

Diagnostic capabilities of the discriminant model for 50 test samples were : 88% for allergic rhinitis, 68% for non-allergic rhinitis (Table 6), and 78% for the total. Compared with the neural network and CBR, this model was more accurate in predicting allergic rhinitis.

4. Covariance structure model

Before analyzing the structural relationship among four factors, a goodness-of-fit test was performed for the CSM. As seen in Table 4, x^2 value was 12.41 and its p-value was 0.995. This indicates that the model-implied variances and covariances were not significantly different from the observed covariance matrix and this strengthens the fit of the model. The x^2/d.f. value was 0.44, which is within the range of an acceptable fit. GFI was 0.994 and AGFI was 0.973, indicating that the model accounted for 97.3% of the observed variances and covariances. CN value was 903, which are much higher than the suggested minimum value of 200. Overall, these measures indicate a very good fit of the model to the sample.

Three types of the effects of patient characteristics were presented in Table 5 : direct effects on diagnosis (γ_{1x}), treatment methods (γ_{2x}), and results (γ_{3x}) ; indirect effects on treatment methods through diagnosis ($\gamma_{1x}x\beta_{21}$), indirect effects on results through diagnosis ($\gamma_{1x}x\beta_{31}$) and through treatment method ($\gamma_{2x}x\beta_{32}$) ; and total effects on treatment methods and results which were a sum of the two effects.

Significant characteristics influencing the diagnosis were skin test on mite and animal ($\gamma=0.573$), skin test on mugwort ($\gamma=0.195$), rhinorrhea and sneezing ($\gamma=0.178$), laboratory test ($\gamma=0.167$), and nasal polyps ($\gamma=-0.143$). Surprisingly, aggravating factor (e.g. cold air) and past history (e.g. asthma) which have been traditionally well known as important caual factors for allergic rhinitis were not significant. Compared with the results of discriminant analysis, all significant factors from the discriminant analysis were also significant in the CSM except septal deviation ($\gamma=0.085$).

Table 4. Goodness of fit test for the Covariance Structure Model

Goodness of fit index	Value
Chi square (degree of freedom)	12.41 (28)
p value	0.995
Chi square / degree of freedom	0.44
Goodness of fit index	0.994
Adjusted goodness of fit index	0.973
Critical N	903

Table 5. Effects of the patient characteristics on diagnosis, treatment methods, and results

	Diagnoisis	Treatment method			Treatment result		
	Direct effect (γ_{1x})	Direct (γ_{2x})	Indirect	Total	Direct (γ_{3x})	Indirect	Total
Runny nose/ itching eye	–	0.072	–	0.072	0.073	-0.005	0.068
Headache and general symptom	–	0.172*	–	0.172	-0.157*	p0.012	-0.169
Rhinorrhea/ sneezing	0.178*	–	–	–	–	–	–
Nasal obstruction	–	-0.071	–	-0.071	–	–	–
Severity of nasal obstruction	–	-0.073	–	-0.073	0.054	0.005	0.059
Aggravating factor (cold air, etc.)	0.060	–	–	–	-0.116	0.003	-0.113
Past history (asthma, etc.)	-0.033	–	–	–	-0.087	-0.002	-0.089
Family history, medication	–	-0.160*	–	-0.160	0.038	0.011	0.049
Septal deviation	0.085	-0.128*	-0.012	-0.14	–	–	–
Nasal polyps	-0.143*	0.434*	0.021	0.455	–	–	–
Skin test (mite, animal)	0.573*	–	–	–	–	–	–
Laboratory test (IgE, etc.)	0.167*	–	–	–	0.015	0.009	0.024
Skin test (Mugwort, etc.)	0.195*	–	–	–	–	–	–
Treatment method	–	-0.146* (β_{21})	–	-0.146	0.056 (β_{31})	0.01	0.066
	–	–	–	–	-0.067 (β_{32})	–	-0.067
Covariance of remaining var(f)		0.435			0.665		0.908

Indirect effect of treatment method $= (\gamma_{1x}) \times (\beta_{21})$

Indirect effect of treatment result $= (\gamma_{1x}) \times (\beta_{32})$ or $(\gamma_{2x}) \times (\beta_{22})$

– : no relationship

* : $P < 0.05$

The significant characteristics influencing the treatment methods at 5% level were : nasal polyps ($\gamma = 0.455$, total effects), headache and general symptom ($\gamma = 0.172$), family history and medication ($\gamma = -0.160$), septal deviation ($\gamma = -0.14$). Positive sign (+) for the path coefficient refers to surgery, while negative sign (−) refers to drug therapy (e.g. antihistamine, steroid, or both). For example, surgery were likely performed for the treatment of the patients with nasal polyps.

In case of treatment result, only headache/general symptom was significant factor with the total effects of -0.169. That is, if patient had headache and general symptom, then he or she did not respond well to the treatment. Unlike the model for diagnosis, this result was quite different from the results for discriminant model.

On the contrary to the previous study, runny nose/itching eye, nasal obstruction, aggravating factor such as cold air, and past history such as asthma did not have any significant effect on diagnosis, treatment methods, and results. The path diagram which represents these structural relationship was presented in Figure 1.

Remaining covariance (ϕ) for diagnosis was 0.435. This means that patient characteristics accounts for 56.5% of variance in diagnosis. Remaining covariance for treatment method and results were 0.665 and 0.908, respectively. Therefore, patient characteristics accounts for only 9.2% of variance in results perhaps due to various confounding factors affecting the results.

Diagnostic capabilities of CSM for the test samples were : 4% for allergic rhinitis, 82% for non-allergic rhinitis, and 44% for the total (Table 6). The reason for such a low accuracy rate for predicting allergic rhinitis may be explained by the fact that the CSM model was developed based on much smaller data set (i.e. 274 cases) and therefore it explained only 56.5% of the variance. Nevertheless, its accuracy rate for predicting non-allergic rhinitis was better than any other models.

Table 6. Comparison of four knowledge acquisition approaches

( ) : percentage

Actual diagnosis made by doctor		No. of matching cases			
		NN	CBR	DA	CSM
Allergic rhinitis	25	18 (72)	12 (48)	22 (88)	1 (4)
Non-allergic rhinitis	25	20 (80)	19 (76)	17 (68)	21 (82)
Total	50	38 (76)	31 (62)	39 (78)	22 (44)

(NN : neural network, CBR : case-based reasoning,
DA : discriminant analysis, CSM : covariance structure model)

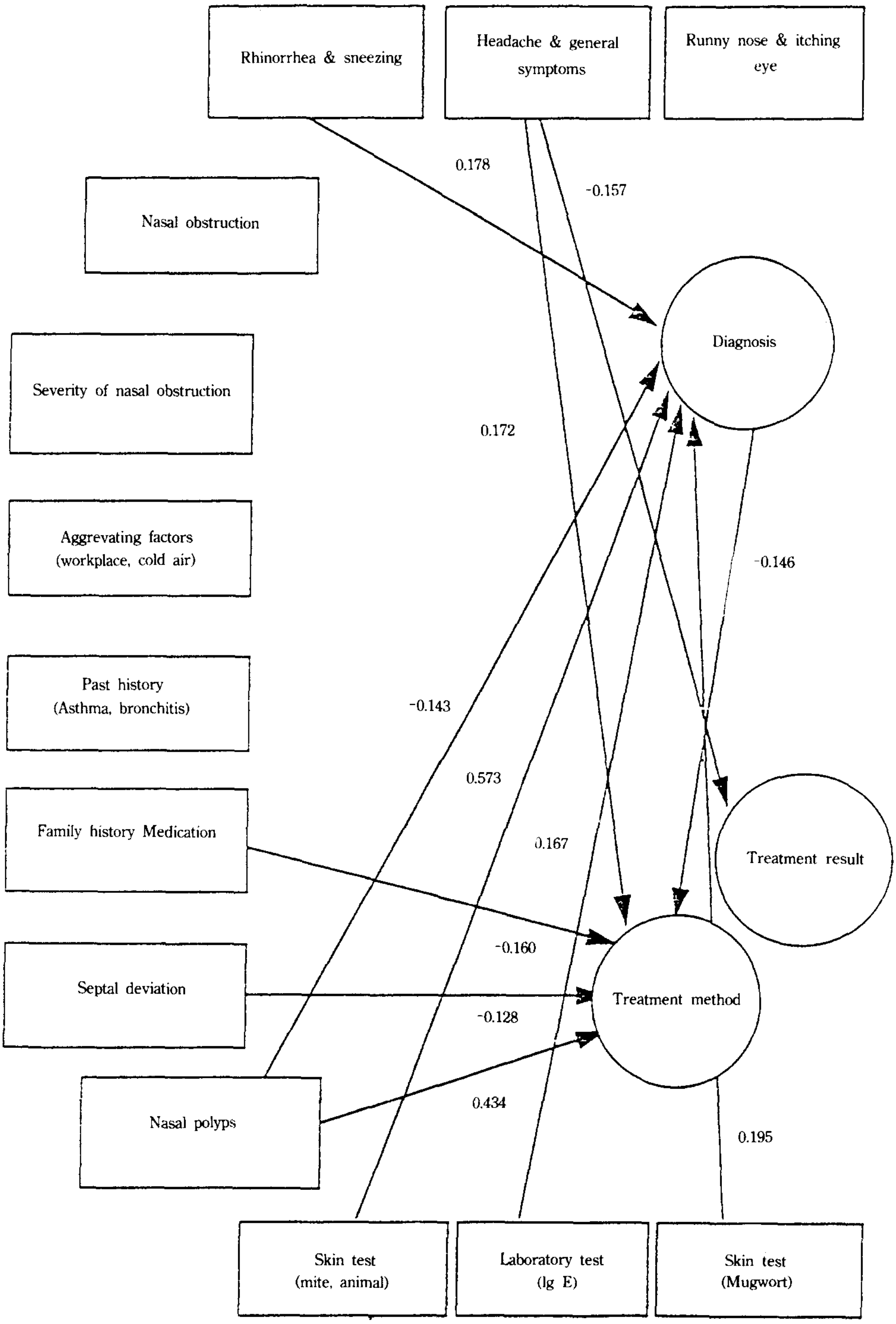

Figure 1. Structural relationship among patient characteristics, diagnosis, treatment methods, and results for allegic rhinitis

Ⅳ. DISCUSSION

Establishment of diagnosis and treatment of allergic rhinitis is multifactorial process involving an assessment of symptoms, severity, seasonal variation, past and family history, laboratory test, and specific diagnostic procedures. There were many studies on identifying the relationship among these various factors to improve effectiveness in diagnosis and treatment. In addition, there were also many studies on developing medical decision support system (MDSS) or medical expert system which provide such information to help doctors improve their decision-making and patient management.

This study compared the diagnostic capabilities of four knowledge acquisition methods that obtain knowledge directly from medical database. Recently, these methods have attracted interests because medical knowledge is sometimes difficiult to describe explicitly.

First such method considered in this paper is neural network. Self-learning mechanism of neural network has been applied to medical expert system as an automatic knowledge acquistion (Astion et al. 1992 ; MaClin et al. 1992). Neural networks and expert systems have various advantages and disadvantages (Hillman, 1990) – expert systems tend to be domain-specific and function extremely well when problems are well defined ; neural networks have a broad response capability based on their ability to provide general classification of a set of inputs. Expert system implementation can be a lengthy process depending on the size of the domain and the range of cases that must be realized; neural networks can analyze a large number of cases quickly to provide adequately accurate responses. Another advantage in the neural network approach is the ability to use experiential data to develop the knowledge base, as oppose to encoding rules for a very complex set of factors over a wide range of values.

Second method considered in this paper is a case-based reasoning (CBR) which is a computer system that solve by analogy with old ones, in a similar manner to medical doctors making decisions (Rich et al. 1991). The CBR enables the MDSS to tap into a medical knowledge source (e.g. medical records, clinical case database) that is often more readily available in hospitals than additional rules, especially only when imperfect rules are available in the medical field. The neural network and CBR have complementary strengths. The neural network systems captures broad trends in the domain, while the CBR systems are good at filling in small pockets of exceptions.

Another knowledge acquisition methods considered in this study were two statistical methods : discriminant analysis and covariance structure modeling (CSM). Unlike other methods, CSM obtains a knowledge by analyzing the structural relationship among patient characteristics, diagnosis, treatment method, and results for allergic rhinitis patients.

Among four knowledge acquisition methods, the discriminant model had the best overall diagnostic capability (78%) and the neural network had slightly lower rate (76%). This may be explained by the fact that neural network is essentially non-linear discriminant model.

While these two methods had similar diagnostic capabilities, contrary to Yoshida's finding (1989), discriminant model performed better than neural network. The discriminant model was also most accurate in predicting allergic rhinitis (88%). This finding suggested that the discriminant model should be given more relevance as a knowledge acquisition tool and be used as reference in the diagnosis of allergic rhinitis. On the other hand, the CSM had the lowest overall accuracy rate (44%) perhaps due to smaller input data set. However, it was most accurate in predicting non-allergic rhinitis (82%).

While the CSM did not perform well in predicting overall diagnosis, it provided useful clinical information about the structural relationships among patient characteristics, diagnosis, treatment methods, and results. In the CSM, significant characteristics influencing the diagnosis were skin test on mite and animal ($\gamma=0.573$), skin test on mugwort ($\gamma=0.195$), rhinorrhea and sneezing ($\gamma=0.178$), laboratory test ($\gamma=0.167$), and nasal polyps ($\gamma=-0.143$). Compared with "share"s in the neural network, aggravating factor (e.g. cold air) and past history (e.g. asthma, rash) which have also traditionally well known as important caual factors for allergic rhinitis were not significant in the CSM. Furthermore, compared with the results of discriminant analysis, all significant factors from the discriminant analysis were also significant in the CSM except septal deviation ($\gamma=0.085$).

There were several limitations in this study. In the CSM, overall diagnostic capability was low and some key patient characteristics were not selected probably due to lack of cases in the sample. Joreskog and Sorbom (1989) suggested that overall fit of the model improves as sample size increases. Since this analysis requires a complete data set for patients (i.e. characteristics, test, treatment methods, and results), data collection period should be further increased considering the drop-out patients during the treatment.

The neural network model developed in this paper can also be further enhanced by using the following approaches. First, the input layer with 98 nodes may be replaced by the three types of determining factors (i.e. skin test, symptom, history) which again form the three distinct networks with the related input nodes. In fact, this approach adds one more layer to the previous neural network model. Second, instead of using dichotomous variables for input nodes, some of them may be replaced by the ordinal variables representing a severity of variable or a degree of importance. Once variables are transformed in such a way, the neural network model can be modified using fuzzy approach.

In addition, the performance of the CBR system can also be improved if the match-weights used in the CBR would be replaced by the "share" (or contribution score) of input variables from the neural network, which was suggested by Garson (1991). Since these two methods have complementary strengths, this approach can further improve diagnostic capability.

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APPENDIX

List of Input Data for the Statistical Analysis

1. Questionnaire Data (42 items)
   1) Demographic characteristics of patients
   2) Symptom
   3) Provoking factor
   4) Aggravating factor
   5) Seasonal factor
   6) Environmental factor
   7) Allergen specific factor
   8) Treatment history
   9) Family history
   10) Miscellaneous
2. Test results
   1) Discharge characteristics (e.g. watery, mucoid, purulent)
   2) Mucosa
   3) Structural anormaly (e.g. polyps, sinusitis)
   4) Paranasal X-ray
   5) Nasal smear (e.g. eosinophil)

6) Ig E

7) Blood eosinophil count (e.g. 300−, 300−600, 600−1000, 1000+)

8) Skin test

(e.g. tree, grass, weed, mold, dust, dust mite, epithelials, food, mugwort)

9) RAST

3. Treatment results

1) Antihistamine

2) Topical steroid

3) Surgery (e.g. Sinus operation, S.M.R., Conchotomy)