Yonsei Medical Journal
Vol. 33, No. 1, 1992

The Development of a Decision Support System for Diagnosing Nasal Allergy

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This paper deals with the problem of improving the capability of the medical dectison support system (MDSS) for diagnosing nasal allergy by integrating the previously developed expert system with the neural network approach. Three knowledge acquisition methods were used to develop the expert system: statistical, rule-based, and the combined approach, Among the three, a combined approach showed the best prediction rate based on discriminant analysis. Using the results of a combined approach as input values, the neural network was developed using back-propagation method. Unlike the expert system, the neural network system provides the resulting allergy status in probabilistic terms. Managerial as well as legal issues were also discussed in this paper.

Key Words: Expert system, artificial intelligent, neural network, nasal allergy, MDSS

For the past decade, the computer has been used in hospitals for a wide variety of functions, ranging from simple patient data management and administration to clinical applications. 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 definded 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 (Shortiffe, 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(Shortliff, *et al.* 1981); INTERNIST for internal medicine (Miller *et al.* 1982); QMR for general medical references (Miller *et al.* 1986) and QMR with speech recognition capability (Shiffman *et al.* 1991). In Korea, medical diagnosis systems were developed for hearing loss (Park *et al.* 1988: Chung *et al.* 1989, 1990; Chae et

Received November, 26, 1991
Accepted March, 25, 1992
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al. 1989a) and for nasal allergy (Jang 1990).

Since the beginning of expert systems techonology, however, knowledge acquisiton 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 knowedge elicited. Much of this was because doctors(experts) tended to communicate shallow knowledge rather than the required deep knowledge structure or they found it difficult to describe procedures and routines. The other major category of knowledge acquisition problems is associated with communication problems-the experts often poorly articulating knowledge representations (Cullen and Bryman, 1988). In addition, knowedge 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).

Neural network is another knowledge acquisition method that can solve some of these problems. Neural network is essentially a type of information processing technology that their design is inspired by studies of the brain and nervous system. Consequently, these systems operate in a fundamentally different manner from traditional computing systems. They are made up of many simple, highly interconnected processing elements that dynamically interact with each other to "learn" or "respond to" information rather than simply carry out algorithmic steps or programmed instructions. Information is represented in a neural network in a pattern of interconnection strengths among the processing elements. Information is processed by a changing pattern of activity distributed across many units. Learning occurs through an interactive adjustment of interconnection strengths based upon information within a learning sample. There are few applications for neural networks in the medical field including the system for diagnosis and treatment of acute Sacrophagal disease (Gallant, 1988).

Expert systems and neural networks 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 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 experimental data to develop the knowledge base, as oppose to encoding rules for a very complex set of factors over a wide range of values. Therefore, integration of an expert system and neural network can exploit the advantages and can be very effective in a complex situation such as the diagnosis of allergy, but such an approach has not really been applied in the medical field. In this paper, an integrated system for the diagnosis of nasal allergy was developed to improve the knowledge acquisition as well as knowledge representation capability of the previously developed allergy MDSS (Jang et *al.* 1990).

There are also managerial as well as legal issues concerning the use of MDSS. How should each physician decide if a system is safe for human use? This is a difficult issue during both development and implementation of a system that makes diagnoses or treatment recommendations. Moreover, a potential danger exists in allowing just anyone to use MDSS. A major concern is that the user might not be sufficiently trained to operate the program properly. Despite the importance of such issues in the medical field, they are rarely discussed in the previous studies. Therefore, we made an attempt to address these issues.

METHODS

Subjects

Subjects for this study were 557 patients who visited the outpatient clinic of the Department of Otolaryngology and the allergy clinic at the Severance Hospital from May 1989 to July 1989.

Knowledge Acquisiton and Representation Methods

In this study, the integrated MDSS was developed in three stages as shown in Fig. 1. In the first stage, an expert system for the diagnosis of nasal allergy was developed using three knowledge acquisition and representation method.

Stage I: Development of expert system:

Statistical approach: The statistical approach obtains knowledge from analyzing questionnaire data on the family history, symptoms, and test results for the 557 patients. Three classes of input data are used in the analysis (see Appendix): questionnaire data; test results; and treatment results. The statisti-

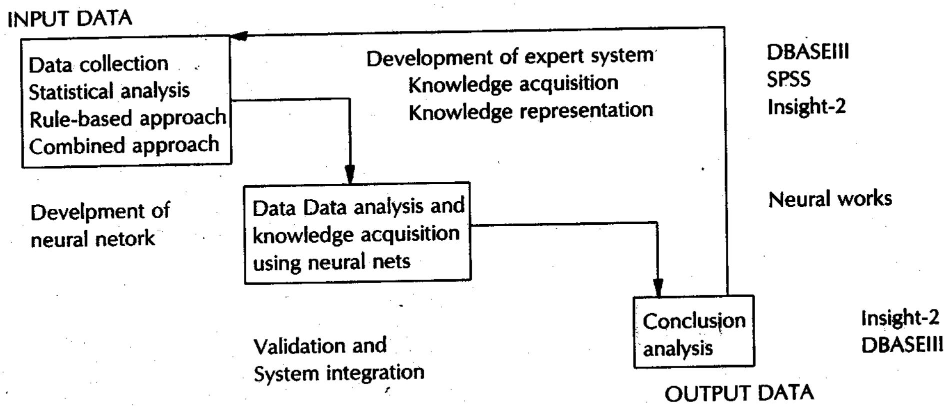

Fig. 1. *Overview of the integrated DSS.*

cal analysis was done in two steps(Chae *et al.* 1989b). First, factor analysis was used to reduce the number of items (or variables) in the allergy questionnaire into several common factors. second, discriminant analysis was used to predict whether the patient has an allergy or not using the factors. While this statistical approach is not widely used in the previous studies, it has an advantage of providing objective and scientific information from a large pool of clinical data.

Rule-based AI approach; Rule-based AI approach obtains knowledge using medical (especially diagnostic) decision rules or heuristics. This is probably the most widely used knowledge acquisition method and is effective in handling exceptional cases in the medical field, although it can have too many unmanageable rules in a complex situation.

Combined approach; This approach attempts to take advantage of both methods. In this study, a combined approach was used by complementing the statistical knowledge base with medical decision rules to account for the exceptional cases among allergy patients.

Stage II: Development of neural network:

In the statistical approach, discriminant analysis predicts allergy diagnosis only in dichotomous terms: either allergy or not. However, there are many cases where the output diagnosis may need to be expressed in probabilistic terms raging form 0 to 1, In this study, the neural network was developed to predict allergy status in probabilistic term using the dichotomous results obtained form the above combined approach. There are two types of neural networks: biological neural network and artificial neural network. A biological neural network is, quite simply, the neurons inside an animal. An artificial neural network is a model that simulates a biological neural network to find out behaviors of a person to solve problems using the relationship between input and output patterns as shown in Fig. 2 (Stanley, 1989). Artificial neural network (simply refered to neural network in this paper) development places a stronger emphasis on experimentation and multiple simultaneous development tracks, iterative refining of network parameters, problem

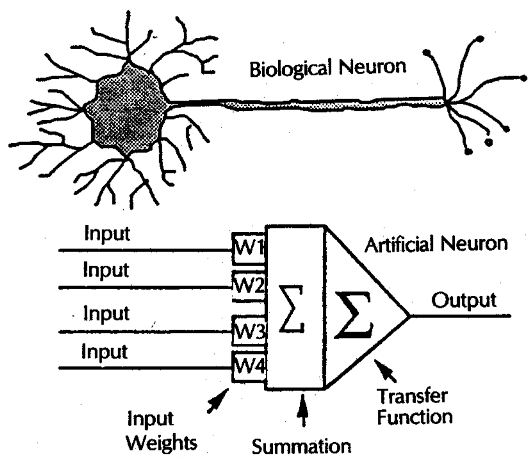

Fig. 2. *Two Types of neural networks.*

redesign and reformulation, and beginning with general solutions and tightening the set of feasible approaches, as seen in Table 1 (Bailey and Thompson, 1990).

Conceptual phase: This phase plans the approach to build the application. In addition, this phase validates the proposed application and selects neural paradigms that may be suitable for meeting the specific requirements. The selection of paradigms is based on the comparison of application requirements to neural-paradigm characteristics as shown in Table 2.

Table 1. Four phases of neural network development

Phase	Activity
Concept	Selecting the application
	Selecting a neural network paradigm
Design	Designing the network
	Determining number of nodes, network size, training
Implementation	Implementing and training network
	Debugging and testing
Maintenance	Integration issues
	System evaluation
	Maintenance considerations

Associative memories are similar to human memory in that they recall complete situations from partial information. Two varieties of associative memory are of interest for neural-network development: auto-and hetero-associative. Auto-associative memories map pieces of data to themselves, memorizing specific information. On the other hand, hetero-associative memories map one set of patterns to another for the classification of patterns. In this study, hetero-associative memory was used.

Another factor for selecting the network is the traning method. The two common classifications of training methods are supervised and unsupervised learning. Supervised learning requires pairs of data consisting of an input pattern and the correct result; training data must therefore contain the solution the network is expected to provide. Unsupervised training classifies input patterns internally and has no need for an expected result. In this study, supervised learning was used since the resulting allergy status was provided in constructing the network.

Design phase: The design phase specifies the initial values and conditions for the selected neural pardigms at the node, network, and training levels, as shown in Table 2. Specifically, decisions to be made at this point include the number of layers, the

Table 2. Characteristics of neural Network pardigms

Paradigm	Associative		Training method		Decision info.		Transfer function	Learning Algorithm
	Auto	Hetero	Sup.	Unsup.	Lin.	Comp.		
Back Propagation			*			*	Sigmoid Hyperbolic	Generalized delta rule
Counter Propagation			*	*		*	Kohonen & Sigmoid	Kohonen & Grossberg
Madaline			*			*	Signum	Delta rule & Max, Min Art2
Art2	*			*		*	Sigmoid	Art2
Kohonen Network		*		*		*	Competitive learning	Kohonen
Boltzmann Machine	*	*	*			*	Varies	Boltzmann
Hopfield Network	*		*		*		Hard limiting	Hopfield
Perceptron			*		*		Perceptron	Delta rule Perceptron

size of each layer, the type of inputs and outputs to expect, and how each layer should be connected. As a convention for the discussion of the size of neural networks, a "layer" is defined as a set of nodes whose weights are actively manipulates; nodes that serve as buffers for input or output will not be counted as layers. Hidden layers act as layers of abstraction, pulling features from inputs. In this study, back-propagation with sigmoid transfer function, which allows a variable number of hidden layers within the network, was selected to increase a neural network's processing power.

Implementation phase: The neural network model was implemented using the neural network development package called Neuralworks Profession II/Plus. Since it has the capability of interfacing with standard ASCII files produced by DBASEIII, integration of the expert system and neural network could be achieved using this capability.

Stage III: Integration of the two systems:

Integration of the expert system, and the neural network was achieved by exchanging output information using ASCII file as mentioned earlier. Since the neural network itself is rather difficult to use for doctors, the integrated system was designed to improve user-interface area so that doctors could access any information without difficulty.

RESULTS

Expert System

Table 3 presents the results of the discriminant analysis for the three knowledge acquisition meth-

Table 3. Results of discriminant analysis for three alternative knowledge acquisiton methods

Methods	Actual diagnosis (rhinitis)	No. of cases	Predicted diagnosis (rhinitis)		Corrrect prediction rate
			Allergic	Vasomotor	
Statistical	Allergic	413	365(88.4%)	48(11.6%)	90.1%
	Vasomotor	144	7(4,9%)	137(95.1%)	
Rule-based	Allergic	413	385(93.5%)	28(5.6%)	92.4%
	Vasomotor	144	14(9.7%)	130(90.3%)	
Combined	Allergic	413	328(92.5%)	31(7.5%)	93.1%
	Vasomotor	144	8(5.6%)	136(94.4%)	

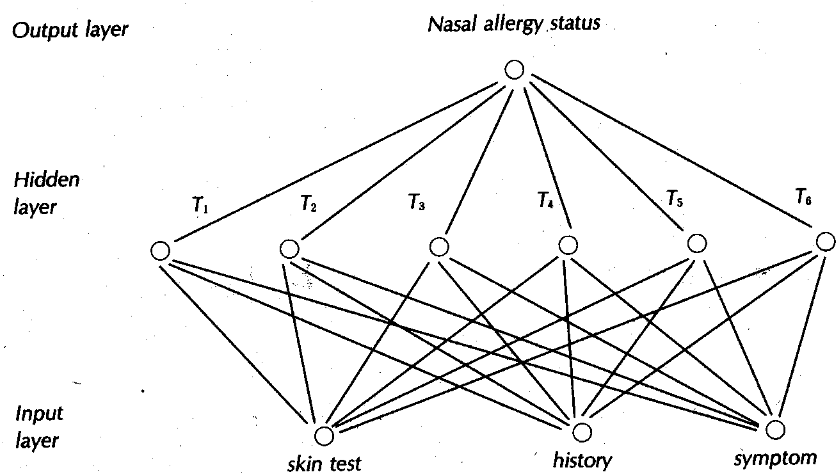

Fig. 3. Neural network model for the diagnosis of nasal allergy.

ods for the expert system. It shows that the overall rates of predicting allergy status gradually increase from the statistical method to the conbined method. While the combined approach has the best overall prediction rate (93.1%), the statistical method has the best specificity (95.1%) and the rule-based method had the best sensitivity (93.5%). Therefore, the selection of a knowledge acquisition method should be dependent upon which rate is the most appropriate for a particular situation.

Neural Network

As seen in Fig. 3. a simplified neural network model was developed to demonstrate how the neural netwrok could provide additional information in the diagnosis of allergy. This model was based on three layers: input layer, hidden layer, and output layer. Each layer has three nodes, six nodes, and one node, respectively. Six nodes were selected for the hidden layer because they produced the most reasonable output. Values for input and output layers are presented in Table 4 using the data from the combined method results. For example, according to the discriminant function of the combined method, when both the skin test and patient history were positive, but the symptom was negative, the result was allergy postitive.

Table 4. Input/output value for neural network model

Skin test	History	Symptom	Allergy status
0	0	0	0.0
0	0	1	0.0
1	0	1	1.0
1	1	0	1.0
1	1	1	1.0

(0=negative, 1=positive)

Neural networks were trained by adjusting the input weights using some automatic algorithm so that the results of stability approximated the desired outcomes for the provided inputs. In this study, back-propagation was used for system learning so that the input weights became modified on the basis of error signals arising from the output layer. Table 5 showed the neural network connection weights, which are the connection weights from each input node to each of the six nodes in the hidden layer. The last column shows how the output layer connections, which are the connection weigths from each of the six hidden nodes to the output node, correspond to the dependent variable, allergy status.

Input layer connection weights indicate the relative importance of causal variables. That is, weights that approach zero indicate situtions in which the investigator may wish to drop that input from the model since it may not have any impact on the output predictions. For example, the connection from

Table 5. Connection weights and shares

Hidden layer	Input layer			Output layer
	Skin test	History	Symptom	
1	-0.51	-0.41	-0.30	-0.87
2	2.19	0.87	0.47	2.80
Weights 3	1.60	0.78	0.41	1.96
4	0.36	0.21	0.01	0.29
5	-1.08	-0.68	-0.41	-1.68
6	-1.99	-0.95	-0.43	-3.04
1	0.06	0.09	0.13	
2	0.79	0.63	0.65	
Shares 3	0.41	0.39	0.40	
4	0.01	0.02	0.00	
5	0.24	0.29	0.34	
6	0.78	0.74	0.64	
Sum	2.28	2.15	2.16	
Relative importance	34.6%	32.7%	32.8%	

Table 6. Selected results of neural network

Skin test	History	Symptom	Result
0.2	0.2	0.2	0.12
0.5	0.5	0.5	0.80
0.7	0.5	0.3	0.94
0.7	0.7	0.7	0.96

input node symptom to hidden node 4 can be dropped from the model because its connection weight was very low(0.01). However, we need to focus on the output rather than the input layer connection weights to examine the relative predictive importance of the independents by partitioning the sum of effects on the output layer. These are represented by the shares using the following equation:

$$\frac{\sum_{j}^{nh} \left(\frac{Ivj}{\sum_{k}^{nh}} Oj \right)}{\sum_{i}^{nh} \left(\sum_{j}^{nh} \left(\frac{Ivj}{\sum_{x}^{nv}} Oj \right) \right)}$$

For each j of nh 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 connetion 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 attridbutable to the given independent variable and thus represents the relative importance of the independent variable. In short, this process partitions the hidden-to-output conncetion weighs of each hidden node into components associated with each input node shares. Table 5 shows that the skin test is the most importance factor(34.6%) for predicting allergy status, followed by the symptoms(32.8%) and history (32.7%).

Table 6 shows the results of examples for fractional input values (i. e. any values between 0 and 1) which are expressed in probabilistic terms. For example, when input values for skin test, history, and symptom were all 0.2(i.e. slightly positive), the output result was 0.12 which indicates that probability of having an allergy was 0.12. Thus, unlike the previous approach, this type of neural net has an advatage of providing the outputs in probabilistic terms when input information is incomplete or not concrete.

DISCUSSION

Implication for further improvement in MDSS

In this paper, the neural net has shown additional outputs in a situation where input information is rather incomplete. As a computing strategy, the neural nets are relatively fault-tolerant. Where neural nets are appropriate, they may be superior to conventional statistical techniques for pattern matching or for classifying dependent variables such as discriminant analysis. To provide more realistic output results, however, the neural net model developed in this paper should be further enhanced using either of two approaches. First, values for the three major input nodes (skin test, symptom, history) should be determined by actual test results and by values from questionnaire, rather than the simple values as seen in this paper. In fact, this approach adds one more layer to the previous neural network model. Second, instead of using three input nodes, the factor scores obtainded form the factor analysis may be used as input values.

As mentioned earlier. the outputs from the neural network can be interpreted as a probability of being Allergic Rhinitis. To be more useful, however, a cut-off point to differentiate whether the patient is Allergic Rhinitis or not can be determined by comparing these output values with the actual diagnosis using past patient records. This cut-off point may also be used to recommend whether the patient needs further laboratory tests or not.

Furthermore, integration of the expert system and the neural network should be further improved by allergy patient database should also be integrated to the system to provide past treatment data to doctors and to accumulate historical data for future research on allergy. Such a database can also provide new information to the system for upgrading the previous models and for further enhancing the system capability by providing treatment information in addition to diagnostic information.

Managerial implication

An expert system should be used in medical practice only if it improves the quality of care at an acceptable cost in time or money or if it maintains the existing standard of care at a reduced cost in time or money. Miller *et al.* (1985) defined improved quality of care by one or more of the following criteria: improved diagnostic accuracy; improved therapeutic results; a patient's sense of well-being; easier and more rapid access to patient information via better record-keeping systems; and better representation of facts in medical records and better documentation of the reasons for the physicians' actions.

Moreover, potential danger exist in allowing anyone who wants to use a computer-based medical decision-making aid have access to it because the user might not be sufficiently trained to operate the program properly. The user must provide medically reliable information as input and be able to override a program's advice if the advice is in error. Access to some programs might therefore be limited to licensed professionals of specific categories. To use a program properly, the user would need the requisite educational background.

As an increasing number of computer programs are being promoted for medical use, ethical and legal problems will also result form the application of such programs in clinical settings. While the legal problems associated with computer programs that provide medical advice have yet to be addressed by the courts, there are several important ethical and legal questions related to the use of computer programs in clinical medicine. Who should be authorized to use such programs, and in what ways? How can doctors and patients evaluate whether a computer programs is safe for use on humans?

The major factor in determining the liabilities of MDSS is the classification of MDSS. If classified as a product, strict product liability will be imposed. But, if classified as a service, professional misconduct or negligence will be imposed (Cook and Whittaker, 1989). Since the physicians' acts of making a diagnosis and of providing therapy have traditionally been classified as services, in all likelihood, adverse outcomes resulting from the use of such systems will be governed by the legal principle of negligence liability. As an increasing number of such systems are expected to be promoted for medical use in the future, there should be proper research on these legal issue to prevent adverse outcomes.

CONCLUSION

In this paper, the medical decison support system for diagnosing nasal allergy was developed by integrating the previously developed expert system with the neural nework approach. Three knowledge acquisition methods were used to develop the expert system: statistical, rule-based, and the combined approach. Among the three, the combined approach showed the best prediction rate based on discriminant analysis. Using the results of the combined approach as input values, the neural network model was developed by the back-propagation method. Unlike the expert system, the neural network provides the resulting allergy status in probabilistic terms. In the future, this network should be further improved by either adding one more layer to the model or using factor scores as input values. Managerial as well as legal issues on the use of the system should also be studied to improve credibility and usefulness of the system.

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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) Miscellaneous

2. Test Results
   1) Discharge characteristics (e. g. watery, mucoid, purulent)
   2) Mucosa
   3) Structural anormaly (e. g. polyp, sinusitis)
   4) Paranasal X-ray
   5) Nasal smear (e. g. esoinophil, mast cell, goblet cell, neutrophil)
   6) Ig E
   7) Blood eosinophil count e. g. 300–, 300+, 600+, 1000+)
   8) Skin test (e. g. tree, grass, weed, mould, dust, epithe, food, mugwort)
   9) RAST

3. Treatment Results
   1) Antihistamine
   2) Antimuscatinic
   3) Prednisolone (oral), Triamcinolone(injection)
   4) DSCG
   5) Immunotherapy (e. g. SDV, HDM)
   6) Surgery (e. g. Sinus operation, S.M. R., Conchotomy