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A Prediction Model for Benign Laryngeal Disease Using Supervised Learning Techniques

Sunghyoun Cho[1], Seonghun Yu[2] and Haewon Byeon[3*]

[1] *Dept. of Physical Therapy, Nambu University, Gwangju, South Korea*
geriatricpt1@naver.com
[2] *Dept. of Physical Therapy, Gwng-ju Trauma Center, Gwangju, South Korea,*
yshjj18@hanmail.net
[3*] *Dept. of Speech Language Pathology & Audiology, Nambu University, Gwangju, South Korea, byeon@nambu.ac.kr*

Abstract

This study developed prediction model for benign laryngeal disease based on machine learning which reflects the characteristics of Korean adults. This study analyzed 8,713 adults (3,801 males and 4,912 females) over the age of 19 who completed laryngoscopic assessment of 2010-2012 Korea National Health and Nutrition Examination Survey (KNHNES). RBF artificial neural network algorithm was used for analysis. The explanatory variables were age, gender, educational level, occupation, income, smoking, binge drinking, and self-reported voice problem. As the result of construction of prediction model for benign laryngeal disease, self-reported voice problem, educational level, income and smoking were significant risk factors of benign laryngeal disease (p<0.05).Construction of prevention model is required to be constructed based on this model to minimize the risks of benign laryngeal disease in Koreans.

***Keywords**: benign laryngeal disease, artificial neural network, laryngoscopic assessment*

1. Introduction

The number of patients with dysphonia who visit medical institutions is on the increase. According to National Health Insurance Corporation, the number of patients who received treatment for their vocal fold nodules in medical institutions increased 15% in 2011 compared to that in 2006 [1]. Considering the fact that some people do not visit medical institution even with the voice problems, prevalence rate of dysphonia is presumed to be much higher. In a study on the adults in local community, 1 out of every 3 adult experiences dysphonia more than once during lifetime [2] and as of 2008, 7.9% of adults over the age of 19 in local communities of Korea had dysphonia [3].

Dysphonia causes unnecessary social expense and increase in medical cost. Economic loss caused by dysphonia amounts to U$ 25 billion in the U.S., ￡ 15 million in U.K. and A$ 52 million in Australia [4]. Like this, although dysphonia not only breaks out frequently in the local community and but also causes enormous social and economic loss, its importance has been neglected for the reason that it is not a major cause of death.

Among dysphonia, benign vocal fold mucosal disorder requires systematic management and prevention since it has the prevalence rate of 3% in adults, which is higher than that of malignant tumor, although it does not have lower survival rate or more fatal aftereffect than malignant tumor [5].

Benign vocal fold mucosal disorders such as vocal nodules, laryngeal polyps, intracordal cysts, Reinke's edema, laryngeal granuloma, glottic sulcus, and laryngeal keratosis are gathered together under the generic term "benign vocal fold mucosal

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disorders," which refers to benign tissues in the laryngeal mucosa, and are typical reasons for dysphonia [1].Benign vocal fold mucosal disorder is known to cause breathy or rough voice problems by changing mucous membrane and tissues of vocal fold [6,7].

Although such benign vocal fold mucosal disorders as vocal nodules and laryngeal polyps are voice disorders most frequently contracted by adults, so far studies on risk factors for benign vocal fold mucosal disorders in Koreans have been insufficient.

Prevention and rehabilitation as well as operation are very important for voice disorders. According to Cohen [2], recurrence rate of dysphonia is 73.3% and it has been reported that even after medical treatment may succeed, its recurrence rate is very high. Hence, successful rehabilitation and prevention of dysphonia requires precise identification of risk factors and constant management.

Meanwhile, machine learning is an algorithm to classify and predict target vector using artificial intelligence. In particular, supervised learning which predicts target vector from the training set has the advantages of effectively solving problems in the future in performing similar tasks based on the experience acquired from inference process and of having high prediction power in figuring out complex risk factors such as voice problems [8].

This study developed prediction model for benign laryngeal disease based on machine learning which reflects the characteristics of Korean adults.

2. Methods

2.1 Data Source

This study analyzed 8,713 adults (3,801 males and 4,912 females) over the age of 19 who completed laryngoscopic assessment of 2010-2012 Korea National Health and Nutrition Examination Survey [9]. National Health and Nutrition Examination Survey introduced Rolling Sampling Survey method so that each of 3 years can be a probability sample which represents the whole country with 3 independent rolling samples. Stratified multistage probability sampling design was adopted based on region, gender, age in the population of registered residents of 2009 and a total of 11,500 samples were surveyed. Items such as education, economic activities, contraction and use of medical institutions were surveyed by individual interviews while health behaviors such as smoking and drinking were surveyed with self-administered questionnaires [9].

2.2 Measurements

The explanatory variables were age, gender, educational level, occupation, income, smoking, binge drinking, smoking, and self-reported voice problems. Ages classified into groups of 19~39, 40~59 and 60 and over. Occupations were classified into economically- inactive, non-manual and manual. Levels of education were classified as elementary school graduates and lower, middle school graduates, high school graduates and college graduates and over. Levels of income for households were classified into four quartiles.

Benign laryngeal disease in this study were defined as vocal nodules, laryngeal polyps, intracordal cysts, reinke's edema, laryngeal granuloma, glottic sulcus and laryngeal keratosis [10].

2.3 Artificial neural network

Artificial neural network is a model composed of numerous processing factors that has hierarchical structure and learns relationship between input and output by repetitively adjusting weighted values through values of past input data and respective output data [11-13].

Artificial neural network model is a modeling method which finds out patterns inherent in data from the data collected in the past through repetitive learning process and its major characteristics are as follows [14,15,16];

First, each neural cell is completely independent from other neural cells. That is, as parallel processing is possible, its calculation can be performed very fast.

Second, its neural network has countless connection strengths and thus, distribution expression and treatment of information can be possible.

Third, various calculations of information is possible with only part of information.

Fourth, it can add new information or change information by adjusting connection strength through continuous learning.

In the application of artificial neural network, it is more important than anything else to perform generalized learning so that learned artificial neural network can perform reliable reasoning on the data unused for learning, not the 'learning' itself which is minimizing the value of objective function for given learning data [17][18], because learned artificial neural network does not have any meaning at all if the learned artificial neural network performs reasoning on the data unused for learning which is different from the pattern inherent in the (parent) population of learning data even when learning is performed on the given learning data while converging on the miniscule value of objective function [19].

This study used RBF artificial neural network which uses Radial Basis Function (RBF) for combination function of hidden layer (Figure 1) [20].

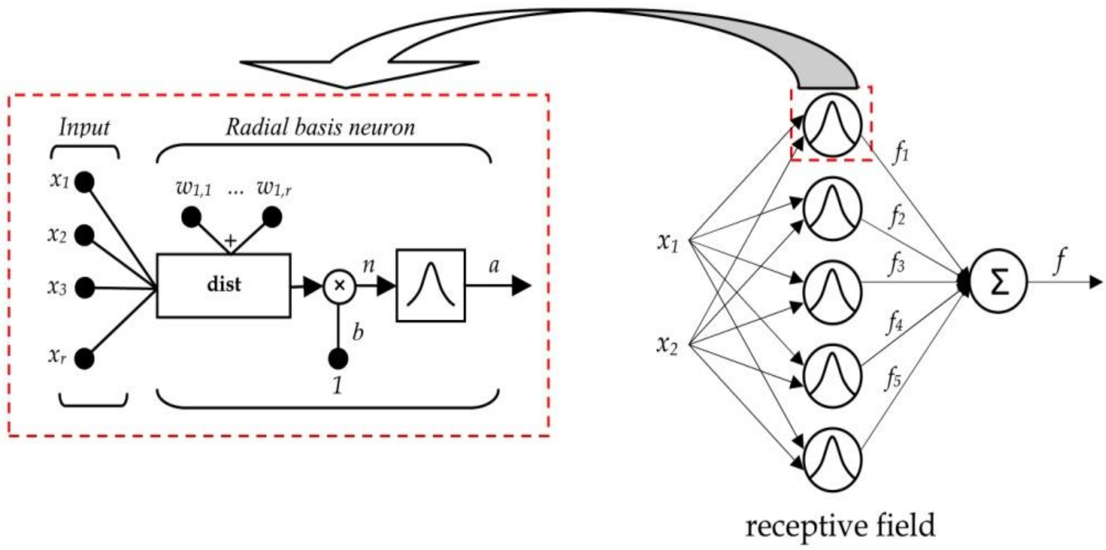

Figure 1. The Radial Basis Neuron and Characteristic Structure of the Radial Basis Function Network. Source: Taniki, D., & Despotovic, V. (2012). Artificial Intelligence Techniques for Modelling of Temperature in the Metal Cutting Process. Rijeka: INTECH Open Access Publisher

3. Results

3.1 General Characteristics of Subjects

General characteristics of subjects are presented in Table 1. Average age of the subjects were 50.3 (standard deviation=16.6). There were more women (56.3%) than men (43.7%) and, as for education level, high school graduates and over (33.05%) and, occupation-wise, economically inactive population (41.4%) were the greatest in number. 58% of the subjects were non-smokers and 72% were drinkers who drink more than once a month. Out of total 8,713 subjects, prevalence rate of benign laryngeal disease was 2.6% (n=230).

Table 1. General Characteristics of Subjects, %

Variables	Total (n=8,713)
Age (mean±S.E)	50.3±16.6
Education level	
≤Elementary school	25.4
Middle school	11.3
High school	33.0
≥College	30.3
Income (home)	
1st quartile	19.7
2nd quartile	26.6
3rd quartile	27.0
4th quartile	26.7
Occupation	
Economically-inactive population	41.4
Non-manual	33.4
Manual	25.2
Smoking	
Non smoker	58.0
Past smoker	21.0
Current smoker	21.0
Alcohol drinking (≥1 per month)	
Yes	72.0
Benign vocal fold disease	
Yes	2.6

3.2. RBF Artificial Neural Network Analysis

As the result of RBF artificial neural network analysis on 59.2% of training sample, 30.8% of test sample and 10.0% of verification sample, 5 hidden layers were drawn out which produce smallest data errors, and sum of square error was 2.7% and, for classification accuracy, training sample proved to be 97.3%, test sample to be 97.2% and verification sample to be 97.3%.

Synaptic weighted network diagram of neural network model is presented in Figure 2. Synaptic weighted value in network diagram demonstrates the relationship among layers and the higher the combined weighted value, the thicker the line between layers. In this model, age, gender, educational level, occupation, income, and smokingwere drawn out as major variables with high weighted values of benign laryngeal disease.

Normalized importance drawn out from neural network model is presented in Figure 3. As the result of normalized importance,age, gender, occupation, incomewere deciding factors of benign laryngeal disease.

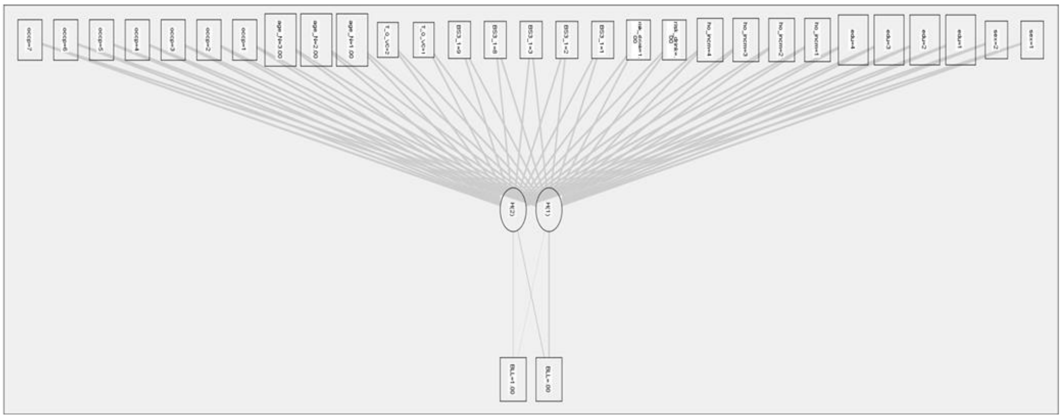

Figure 2. Synaptic Weighted Network Diagram

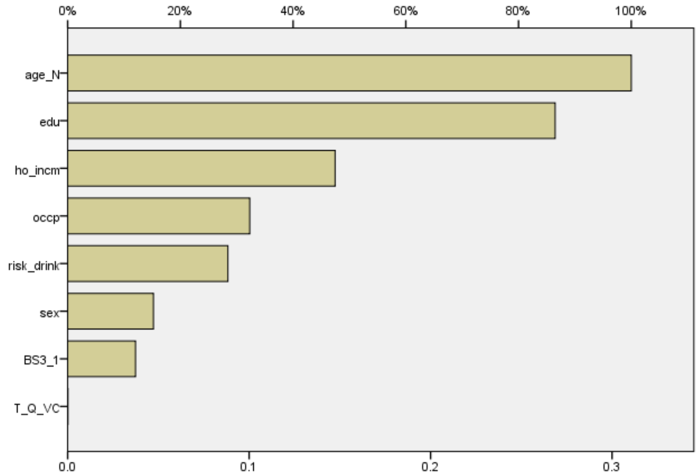

Figure 3. Normalized Importance from RBF Artificial Neural Network Model

4. Conclusions

In this study, self-reported voice problem, educational level, income and smoking were significant risk factors of benign laryngeal disease.Construction of prevention model is required to be constructed based on this model to minimize the risks of benign laryngeal disease in Koreans.

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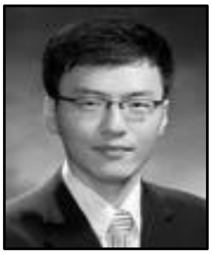
Authors



Sunghyoun Cho, He received PhD degree in Physical Therapy from Daegu University. He is a professor in Department of Physical Therapy in Nambu University, Gwangju, Republic of Korea. His recent interests focus on Biomechanics and Therapeutic exercise.

Sunghun Yu, He received PhD degree in Physical Therapy from Dongshin University. His recent interests focus on Psychology and manual therapy

Haewon Byeon, He received DrSc degree in Biomedical Science from Ajou University School of Medicine. He is a professor in Department of Speech Language Pathology & Audiology and director of Speech Language Pathology Center in Nambu University. His recent interests focus on health promotion and biostatistics.