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Large database analysis of out-of-hospital cardiac arrest using ensembled neural networks

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Abstract: The purpose of this study is to use seven different sensitivity analyses to find out the important variables to establish a comprehensive and objective assessment method. After pre-filtering, we obtained 4095 data for building this ensembled neural networks **(**ENN) model. The data has been divided into 60% data for training, 20% data for validation, and 20% data for testing. The eleven inputs, including response time, on-scene time, patient transfer time, time to cardiopulmonary resuscitation (CPR), CPR on the scene, using drugs, age, gender, using airway, using automated external defibrillator (AED), and trauma type, and one output variable have been selected as ENN model structure. The results have been shown CPR on the scene, using drugs, on-scene time, and using airway in the top four of these 11 important variables. Moreover, these four variables have also been shown significant differences when we use traditional one variable statistics analysis for these variables.

Keywords: Emergency medical system, ensembled neural networks, sensitivity analysis

I. INTRODUCTION

Fire Department, New Taipei City Government started to build a new system of recording pre-hospital cardiopulmonary stop patients' data in 2007. Until June 2011, the system has collected more than 9,000 data of the OHCA (out-of-hospital cardiac arrest) patients, including patients' basic characteristics, emergency treatment, the basic information of ambulance staff and patients' recovery treatment. Therefore, this study will target on analyzing out-of-hospital cardiac arrest patients data, and focus on the distribution of the incident, treatment, and the relationship between survival rate and the relevant characteristics of OHCA patients. Because of many uncertain factors, irregular non-linear characteristics, and the complex relationship of variables, it is difficult to use traditional mathematical equations and analytical methods. Hence, it must more carefully select the characteristics of the method. According to our previous studies [1-3], artificial neuronal network (ANN) is one of the most popular systems to deal with the nonlinear and non-stationary problems. It can be used to model the complex relationships between the inputs and outputs data of the system. An ensembled neural network (ENN) is a learning paradigm where a collection of a number of neural networks is trained for the same task. One theory behind using ENN is that several less accurate networks that are diverse can be combined into a more-accurate ENN. Moreover, we use seven different sensitivity analyses to find out the important variables to establish a comprehensive and objective assessment method. Then, we can understand which variables cause the survival rate or Glasgow Coma Scale (GCS) changes by build a model of ENN.

II. METHODOLOGY

(A) Choosing variables

According to previous research [3,4] and the information recorded in the OHCA patients in Fire Department of New Taipei City Government, the eleven inputs, including response time, on-scene time [3], patient transfer time [4], time to cardiopulmonary resuscitation (CPR), CPR on the scene, using drugs, age, gender, using airway, using automated external defibrillator (AED) [5], and trauma type, and one output variable have been selected as ENN model structure.

(B) Data pre-processing

Although we have 9000 patients in the database, we have only 4,095 complete data in the database after data cleaning. Then we build an ensembled neural network. The data is divided into three parts which were 60% data for training, 20% for validation, 20% for testing as shown in Fig. 1. Testing data do not need to pass through neural network to learn, so we do not sample data by random. The remaining 80% data are divided into 60% of training data and 20% validation data by random sampling. Then we selected topology structure of neural network model, and trial and error can help us for screening each structure [6]. There is a classic topology called pyramid. In many literature records, this method has better convergence and predictability. The pyramid means that the neurons of input layer are more than the neurons of hidden layer, and the neurons of hidden layer is more than the neurons of output layer [7].

(C) ROC analysis

We don't know the performances of model after building neural network model. So we applied ROC (receiver operating characteristic) curve analysis to find out the threshold at each model and estimate the discrimination power of the prediction models. We calculated the sensitivity (SEN), specificity (SPE), positive prediction value (PPV), and negative prediction value (NPV) of each model at the best threshold. Then we use this threshold to separate 0 and 1 for the each output that 0 is death and 1 is alive. Finally, we calculated total accuracy as the discrimination power of the prediction models.

(D) Ensembled neural network model

Although neural network is powerful, it's unstable due to random initial weight problems. Scholars have criticized for this long time. Ensembled neural networks are built by the group of neural networks to solve this problem. The topology structure of ENN is chosen one hidden layer with 8 nodes via trial-and-error method so that we choose 11-8-1 structure for this model. Moreover, the one output variable has been selected 5 different conditions (i.e., 2hr or 24 hr survival rate, or 24hr, 48hr, and 72 hr GCS). Each training data and validation data are used to train 20 networks with different initial weights. Then, 100 artificial neural networks (ANN) have been trained for each network. The learning effect of each network is tested by the testing data to examine the generalization of the network, and the best network in each training data and validation data is selected to be combined into the ensembled model [8, 9] as shown in Fig. 1.

(E) Sensitivity analysis

Sensitivity analysis can find the important parameters in the model. It works by observing the input variables how to impact on the output. We use seven different methods for sensitivity analysis. Firstly. We use the Morris method which is a randomized design that has proved to be an efficient and reliable technique to identify and rank important variables [10, 11]. Secondly, there are three methods to improve Morris method which are set the minimum, maximum, and mean values, while other variables have not changed. The root means square error of the network is assessed. Then the changed of RMSE is calculated. We can rank the input variables by the changed of RMSE. The more important variable is bigger changed. Finally, the rest three methods which are Perturb's method [13], connection weights [14], and Garson algorithm [15], can be seen more details in our previous study [16].

III. RESULTS

We have built five ensembled neural network models for different outputs. After building this ENN model, we use testing data to calculate this five outputs accuracy and the results show the accuracy is 68%, 76%, 80%, 86%, and 89%. The highest accuracy is 72 GCS model of prediction, and we use this model to do seven different sensitivity analysis. Finally, we use vote method to sum these 7 sensitivity methods via adding together the index number of ranked variables in seven methods of sensitivity analysis, and the more important variable has a smaller vote number. The results have been shown CPR on the scene, using drugs, on-scene time, and using airway in the top four of these 11 important variables as shown in Table 1. Moreover, these four variables have also been shown significant differences when we use traditional one variable statistics analysis for these variables.

IV. CONCLUSION

In conclusion, although the results of top four important inputs are consistent with one variable statistics analysis, the result of sensitivity analysis still has not been verified by experts. Hence, a comprehensive discussion with medical doctors who are experts in emergency medical system is still needed, perhaps to refine the ENN model or methods of sensitivity analysis, and certainly to see how widely the model and these methods are applicable.

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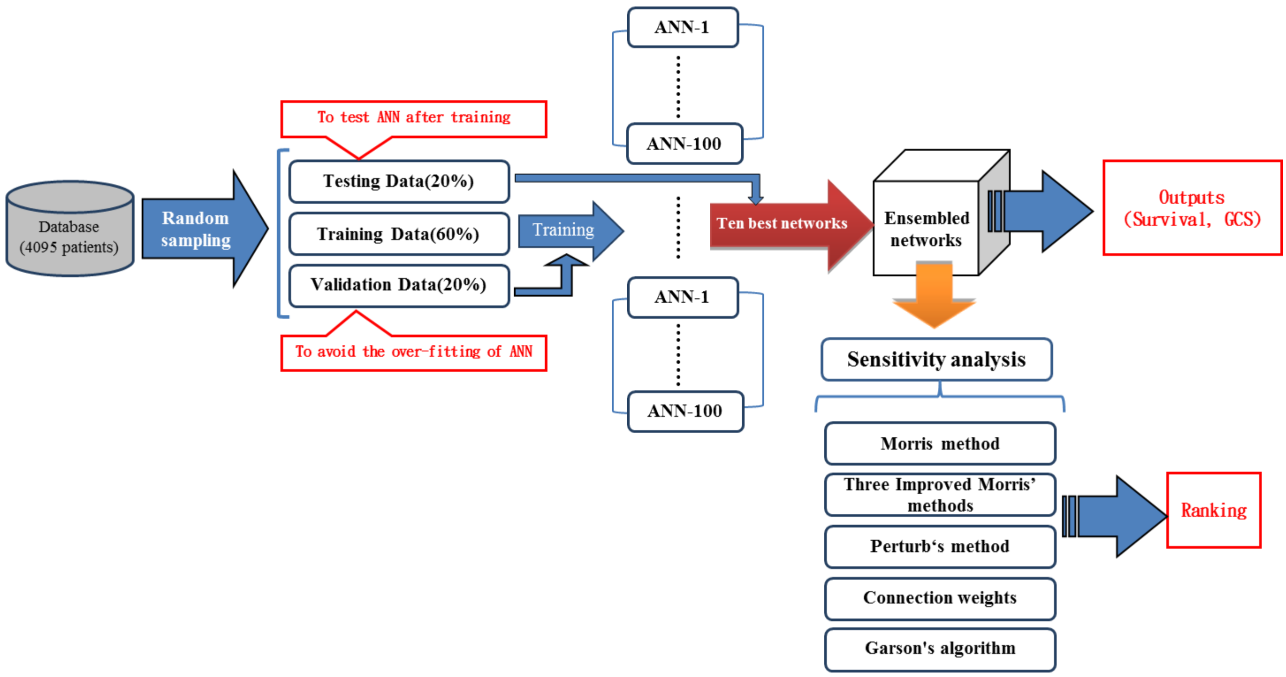

Fig. 1 The flow diagram of ensemble neural networks and sensitivity analysis

Table 1 The ranking of input variables according to seven sensitivity analyses
(Note of Table: SA means sensitive analysis)

Input Variables	SA (Morris Method)	SA_min	SA_mean	SA_max	SA_noise (Perturb Method)	Connect weights	Garson's algorithm	Ranking	One variable statistics analysis
Response time	5	8	7	10	4	7	4	7	*P* > 0.05
On-Scene time	1	4	9	6	1	3	10	3	*P* < 0.05
Patient transfer time	6	7	6	3	9	4	6	6	*P* > 0.05
Time to CPR	11	2	1	1	10	4	11	5	*P* > 0.05
CPR on the scene	3	1	2	2	8	1	1	1	*P* < 0.05
Using drugs	2	3	5	5	6	7	5	2	*P* < 0.05
Age	9	10	11	7	5	4	8	10	*P* < 0.05
Gender	7	6	10	10	3	10	2	9	*P* > 0.05
Using Airway	8	9	3	7	2	2	7	4	*P* < 0.05
Using AED	10	11	8	3	6	9	9	11	*P* < 0.05
Trauma type	4	5	4	9	10	11	3	8	*P* < 0.05