An Intelligent System for Prioritising Emergency Services Provided for People injured in Road Traffic Accidents

Mohammad Taghi Taghavifard¹

Sharareh Rostam Niakan Kalhori²

Pegah Farazmand^{3*}

Khatereh Farazmand⁴

¹Department of Management, Faculty of Management and Accounting, Allameh Tabataba'i University, Tehran, Iran

²Department of Health Information Management, Faculty of Allied Medical Science
Tehran University of Medical Sciences, Tehran, Iran

³Department of Management, Faculty of Management and Accounting, Allameh Tabataba'i University, Tehran, Iran

⁴Department of Health, Faculty of Health, Shahid Beheshti University of Medical Sciences, Tehran, Iran

*Corresponding author: Pegah Farazmand, e-mail: farazmand.atu@gmail.com

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Abstract

Excessive road traffic accidents are the cause of referrals of a large number of injured people to hospitals. However, shortage of resources does not allow caring for all of them at the same time. Therefore, injured individuals should be prioritised by a triage unit. Patients with serious life-threatening conditions should be sent as the first priority to the emergency department to receive required care. This paper aims to design a triage model for categorising injured individuals using two different methods: Neural Network (NN) and Adaptive Neuro-Fuzzy Inference System (ANFIS). The models were built with a data set of 3015 data designed by Iranian medical experts and were based on patients' general appearance, vital signs and chief complaints. When a patient presents to the triage unit, the system analyses the data given and patient's emergency status can be reported straightaway. This reduces the triage time and the queue of patients at the emergency department. Both models were tested by 3 groups of data with a total number of 417 data. Reliability and validity were assessed. Results showed that overall ANFIS model performed better in categorising patients.

Keywords: Adaptive Neuro-Fuzzy Inference System (ANFIS), Neural Network (NN), Intelligent System, Traffic Accidents, Triage

1. Introduction

Accidents are inevitable events in daily life. Road traffic accidents threaten human life more than any other events. They cause apparent health and social problems in developed and developing countries. This becomes even more important considering that most of the victims are usually young and healthy (Jahangirfard et al, 2014). According to WHO¹ reports, nearly 3400 people die on the roads every day. Tens of millions of people are injured or disabled every year (Pietrasik, 2014). Accidents result in Disability Adjusted Life Years (DALY), Years Life Lost (YLL) and Years Life Disability (YLD), imposing high pressure on health budgets of countries (World Health Organization, 2014). Iran deals with a lot of problems related to road traffic accidents which according to UNICEF² reports cause thousands of injuries and deaths every year and cost billions of dollars (UNICEF, 2014). Recent Iranian Legal Medicine's site statistics showed that number of deceased and injured people due to road traffic accidents in during 12 months of 2014 were 16872 and 304485, respectively (Iranian Legal Medicine Organization, 2014). According to Paravar et al (2013) and Tavakoli Kashani et al (2012), Iran has one of the highest rates of road traffic accident in the world and around 55 people die in Iran daily (Trend News, 2013).

The important fact is that due to a huge number of accidents, a large number of people with dangerous conditions are referred to hospitals every day and every hour. At the same time relatives might wish for their patients to be sent to the emergency department and considered as the first priority. Also, in some cases, two or more injured people are taken

¹ World Health Organization

² United Nations International Children's Emergency Fund

to hospital at the same time while it may be impossible to provide immediate care for all of them due to shortage of resources. In all these cases, those injured with severe life threatening conditions should be considered as the first priority. Therefore, in every hospital there is a unit called the triage unit where patients' conditions are investigated and classified based on their priorities and available resources before being sent to the emergency department.

In Iran, triage instructions have been developed in the form of algorithms, tables and guidance booklets and the documents are held in the triage unit. Many of the triage activities including patient classifications are done by the triage unit nurses based on their own experience and there is no smart system available. This paper tries to design a smart system to help assess the condition of injured individuals in a road traffic accident and to priorities them in order to receive efficient care in time. It also helps to reduce waiting time in triage units of hospitals. The performance of this system is a simulation of the performance of triage units and its aim is to categories patients according to their vital signs. In addition to hospitals, this system can also be used in smaller health settings.

In general, the objective of this article is to propose an intelligent system using ANFIS -as a hybrid model- for prioritizing injured people taken to the hospital triage section based on their vital signs and providing timely services to them.

2. Review of Literature and Previous Research

Triage, originating from the French word *trier* meaning 'to sort,' is a process of prioritization (Bottrill et al, 2008). In fact, it is used to identify the level of urgency of care and to treat patients based on their triage level (Farrohknia et al, 2011). Triage helps to manage the turnover of patients more reliably and securely in situations where clinical needs are beyond the capacity of the units. There are different assessment methods for evaluating patients in triage units. Triage Revised Trauma Score (TRTS) is one of the most important methods. TRTS is an important approach for evaluating patients in triage based on three important vital signs, i.e. respiratory rate, systolic blood pressure and Glasgow Coma Scale (GCS) and divides patients into four groups (Rehn et al, 2011; Lichtveld et al, 2008; Paravar et al, 2013). It has been used in several studies and is reliable in determining patient's status (Al-Salamah et al, 2004). However, there are different studies available regarding triage and categorizing patients and every study adopts a different approach for this purpose. This section reviews a number of studies about triage and the used methods in categorizing patients. It also introduces different models for designing an intelligent system to categories patients.

Lin et al (2011) used cluster analysis (a combination of SOM and K-mean) and rough set theory along with ROSE2 (Rough Sets Data Explorer) software to extract information from a large number of unknown data in a hospital's triage unit database in Taiwan. This study tried to analyse a large number of data to extract unknown information and create a model in order to simplify the data while preserving its accuracy in categorizing that information. The accuracy of this work was 0.937.

Xu et al (2014) used self – organising map (SOM), k-means and hierarchical methods to categorise patients according to the medical procedures performed and compared these methods. This aimed to improve the management of emergency resources and to use a data-driven method to categorise patients who used similar resources. The results showed that the SOM model had a good performance in this patients' group.

Azeez et al (2013) used ANFIS and neural networks to categorise patients via Objective Primary Triage Scale (OPTS). In this model, when a patient with emergency condition was referred to hospital, his/her vital signs were recorded in a system. Then, the recorded data were analysed and his/her condition was immediately determined. This model was designed by 2223 data with 20 inputs that were related to patients' vital signs. It helped to save time to a large extent and reduced the work load of nurses and physicians during triage process. The efficiency of neural network and ANFIS in categorising patients was 99% and 96%, respectively. This study showed that neural network had a better performance with more inputs compared to ANFIS.

Golding et al (2008) used Fuzzy-Q learning and genetic algorithm and developed an automated system for triage. This study introduced a new system to automate accident and emergency center triage and utilized the triage score along with an artificial intelligence appraisal of patient-doctor time to optimize the queue order. A fuzzy inference system was used to triage patients. A similar system appraised the time and adapted continuously through fuzzy Q-learning. Then with the use of a new method based on genetic algorithms optimal queue order was found. These contents were joined in a simple graphical user interface. In this study, they used Cape Triage System (CTS) to train a number of variables including systolic blood pressure, heart beat, temperature and respiratory rate. The triage nurse recorded CTS signs of patients and informed the physician who then determined the category of every patient. They could not perform live tests but simulations showed that the average waiting time could be reduced by 48 minutes and urgent patients were given priority.

3. Method and Materials

3.1 Selection of Triage Assessment Method

In the process of data collection in our study, it was necessary to determine the type of the triage assessment method as well as the vital signs required for designing it. Therefore, we evaluated different triage assessment methods. Published studies and experts' opinions were used to identify and select a triage assessment method. Seeking experts' opinions was done through personal interviews with the physicians and trainees of the emergency departments in different hospitals in Iran. Based on the obtained opinions as well as available resources in the case study hospital, TRTS method was selected as the assessment method for two reasons: It dealt with fewer but important vital signs and those signs were registered in the files of the chosen patients for the study.

3.2 Determination of Input and Output Variables

When triage assessment method was selected, input and output variables were determined in accordance with the selected method. The variables were:

A) Input variables

Respiratory Rate: This is the number of breaths per minute. It is usually measured when a person is at rest by counting the number of breaths (the rising of the chest) for one minute. Respiratory rates could increase with fever, illness, and other medical conditions. In addition to respiratory rate, it is also important to check whether a person has any difficulty breathing. Normal respiratory rate for adults ranges from 12 to 16 breaths per minute (Johns Hopkins Medicine, 2014a).

Systolic Blood Pressure: The highest value of blood pressure is called systolic pressure. It refers to the pressure inside the artery when the heart contracts and pumps blood through the body (Johns Hopkins Medicine, 2014a).

GCS or Glasgow Coma Scale: The Glasgow Coma Scale (GCS), which is the foundation of the Trauma Score, Trauma and Injury Severity Score, and the Acute Physiology and Chronic Health Evaluation scoring systems, requires a verbal response (Meredith et al, 1998). It is used to determine the depth, duration and intensity of consciousness drop in people >1year of age. This scale is generally used in patients with brain damage, emergency conditions and other consciousness disturbing situations. The lowest possible GCS is 3 (deep coma or death), while the highest is 15 (fully awake person).

B) Output Variables

Output variables are the categories of patients which are determined based on input variables:

Category 1 (urgent): patients with serious life threatening conditions who will die in <5 minutes if they don't receive imminent medical intervention.

Category 2 (emergent): patients who will die or suffer serious damages within 1-2 hours if they don't receive medical interventions within 5 to 60 minutes.

Category 3 (delayed): patients who can survive with minimum possible intervention and are not in a critical condition. They can receive care after emergent patients.

Category 4 (deceased): patients with no signs of breathing and blood pressure and no response to external stimulus.

3.3 Data Collection

The case study hospital provided only 139 real data regarding patients with car accidents and emergency conditions. This data size was inappropriate for training the proposed model but it was appropriate for testing it. To collect more data, experts' experiences and scientific resources were used. With the help of the experts who were familiar with TRTS assessment method and dealt with injured people with different emergency conditions, 3015 data concerning patients' conditions in accordance with TRTS assessment method were collected. At first, different conditions of patients as well as their categories were determined by the trainees of the emergency unit. Then, the data were evaluated by the relevant physicians and the confirmed data were registered in an excel file. This data set (excel file), having been prepared in accordance with experts' opinions and scientific resources, covered various conditions that were likely to be experienced during real emergency conditions. It contained conditions from category1, category 2, category 3 and category 4 patients. The only problem was that there was only one condition in category 4 patients and therefore it had to be considered as an outlier data in the process of training the model. To solve this problem, this data was repeated for a given iteration (15

iterations) in accordance with a test performed in the data set. The prepared data set was then used to train the model.

3.4 Model Selection

Considering the performance of triage models, explained in the history section, neural network and ANFIS models were selected for simulation. The reason for choosing ANFIS is that ANFIS -as a hybrid model- takes advantage of both Neural Network as an advanced forecasting tool and Fuzzy system considering linguistic variables.

3.4.1 Neural Network model

Artificial Intelligence (AI) is considered to be a subdivision of computer sciences which is concerned with simulation, extension and expansion of human intelligence (Shi et al, 2006). There are several different types of artificial intelligence. The most common is the artificial neural networks which are one of the most accurate and widely used forecasting models (Gonzalez-Carrasco et al, 2012). Neural networks are made of simple functional components with parallel functions. The components have been inspired by biological neural systems. Neural networks are adopted on the basis that the inputs are in conformity with the targets so that the network output and the desired output (target) conjoin with each other. Generally, a large number of such inputs and outputs are used to train the network through this process which is called supervised learning.

At the beginning of the study, desired output was already available as the data collected for training the model was provided by the experts based on different conditions of patients. Also, the categories of patients were determined as the output. Therefore, since learning is a trait of neural networks, a supervised learning-based neural network needed to be used for designing purposes. This type of learning assumes that every iteration of learning algorithm provides the desired output for the system and network errors become less and less by changing weights.

Therefore, perceptron network with back propagation algorithm (Multi-Layer Perceptron) was used where desired output was applied to the network. MLP is the most commonly used static network, in which the inputs along with the desired output are presented to the network, and the weights are adjusted so that the network produces the desired output (Moghaddamnia et al, 2009). The MLP network has three layers: input layer, a hidden layer and an output layer (Hagan et al, 1996).

In this study, the inputs were different conditions of patients in terms of respiratory rate, systolic blood pressure and Glasgow coma scale as well as the category of every patient (target). The inputs were applied to the considered network and they trained the network. There were 10 neurons in the hidden layer of the network. This value, by which the network had the best performance and convergence, was selected after performing different tests. The transfer functions used in this network were hyperbolic tangent sigmoid³ transfer function in the hidden layer and linear⁴ transfer function in the output layer (Hagan et al, 1996). Figure 1 shows the multilayer neural network used in the study. As explained before, this network was trained by 3015 data and the training error was 0.007.

Figure 1: Neural Network in this study

³ $a = \frac{e^n - e^{-n}}{e^n + e^{-n}}$
⁴ $a = n$

3.4.2 ANFIS Model

In computational problems of the real world, a combination of solutions generally show a better performance compared to individual use of them. This reality has led to the creation of such systems within Neuro-Fuzzy computation pattern. These systems use neural networks to identify patterns and adopt them to environmental changes. In addition to neural systems, fuzzy inference systems are used to systematically describe human knowledge, conclude problems and make a proper decision. Among different combinations of soft computing, the combination of fuzzy logic and neural networks within the Neuro-Fuzzy framework is a dominant combination and is named as ANFIS system.

Before designing an ANFIS-based system, the initial decision was to use a fuzzy model to design our triage system. However, fuzzy system had an apparent problem. It could hardly adapt to problems within TRTS assessment system and it was impossible to provide an ideal solution by just using the fuzzy system. Investigations revealed that a fuzzy system should be trained and its adaptability should be promoted in order to be able to show a proper performance in this field. The selection of a membership function plays a significant role in the performance of a system and sometimes it is difficult to identify a correct membership function in the process of modeling a system. In such cases, it is better to use a combined system such as ANFIS. ANFIS is a fuzzy system that uses a neural network to promote its adaptability and reduce system error.

Therefore, we decided to use ANFIS system to design our triage system and we compared its performance with that of neural network. Initially, the data set provided by the experts was introduced to the ANFIS model. Then, considering the inputs and outputs, determined by the experts, the model identified the proper membership function of every input and output. Generally, ANFIS consists of 5 layers. In the first layer inputs are introduced to the system and fuzzification is done in accordance with Gaussian membership function. The second layer deals with the inference of Sugeno and formulating rules. Normalization is carried out in the third layer where the contribution of every rule to the contribution of all rules ratio is determined. The fourth layer includes adoptive nodes. It calculates the output of every node using result parameters. Finally, the fifth layer includes the output node which states the final value of the output as the sum of the outputs of previous layer nodes. ANFIS learning algorithm is a hybrid learning algorithm and includes both gradient descent algorithm for updating nonlinear parameters of the network and recursive least square algorithm for adjusting network weights (Jang, 1993; Hosseinpour et al, 2013; Abdulshahed et al, 2015).

Considering the mentioned structure, the data set of patients' conditions with 3015 data was applied to the ANFIS. The data set trained our ANFIS model where training error was obtained as 0.065. Figure 2 shows a schematic view of our ANFIS model.

Figure 2: Adaptive Neuro-Fuzzy Inference System(ANFIS) of the study

3.5 Models Training

As it was mentioned before, the training error of neural network and ANFIS were 0.007 and 0.065, respectively. Initially, it seemed that neural network had a better training performance. However, evaluating the test results of the trained data in ANFIS revealed that the trained data had efficiently covered the data in the patients' conditions data set. In order to

assure the performance of the two models in training the data set, all conditions stated in the data set were assessed by both models. Although neural network had a lower training error which initially made it to be seen as a superior training model, it could not predict any of the patients' categories. Also, after rounding the obtained numbers it was revealed that neural network had mispredicted some categories which was the main training error of this model.

Regarding ANFIS, although it showed a higher training error, it could accurately predict the categories especially category 3. Therefore, even after rounding the obtained numbers no mispredicted category was seen. It was revealed that the higher training error of ANFIS, compared with neural network, was due to approximate values of the results. In fact, after rounding the obtained values the training error of ANFIS became lower than that of neural network and its accuracy rose.

Therefore, in order to make sure about the performance of both models it was decided to round all values obtained by both models and to continue the evaluation process based on the rounded values. This helped us to determine the prediction accuracy of the models more efficiently. Both models as well as 1500 training epoch were designed by MATLAB software. The other procedures such as data collection and evaluating results were performed by EXCEL and SPSS software.

4. Results and Discussion

To test the models, three data groups each with equal number of 139 data were created. Each group was created for a given purpose. The first group was the real data of injured people referred to the case study hospital. This data was tested in order to determine which model shows a better performance in real data with respect to our data set of different conditions. The data of category 1 and 2 were included in this group and it contained no data from category 3 and 4. The data were collected in random without any intervene. The second group data was extracted from the trained data set and applied to both models in order to test the results. This data was tested in order to confirm that if a more comprehensive data set was used, so that any introduced patient data to the system could be found in the data set, there would be less error and higher accuracy in the system. The third group of data did not exist in the trained data set and was prepared by the team just for testing. This was in order to test a larger number of data which did not exist in the trained data set. It was collected by simple random method and contained data from all categories. Table 1 shows assessment results.

Table 1. Assessment Results

TEST(3)		TEST(2)		TEST(1)	
ANFIS	neural network	ANFIS	neural network	ANFIS	neural network
MSE=0.05036	MSE=0.18705	MSE=0.0072	Error=0.022	MSE=0.151079	MSE=0.151079
RMSE=0.22441	RMSE=0.4325	RMSE=0.085	RMSE=0.147	RMSE=0.389	RMSE=0.389
Accuracy=97%	Accuracy=91%	Accuracy=99.6%	Accuracy=99%	Accuracy=91%	Accuracy=87%
96%	ANFIS	92%	neural network	performance accuracy average	

The above values have been derived from the following relations Chockalingam (2007):

- 1) $MSE = \sum_{i=1}^N (f_i - f_i^A)^2 / N$
- 2) $RMSE = \sqrt{MSE}$
- 3) $Accuracy = 1 - \text{abs}(f_i - f_i^A) / f_i$

Where MSE is Mean Square Error, f_i is real data, f_i^A is predicted data, N is the total number of data, RSME is Root of Mean Square Error and accuracy is the accuracy of performance.

According to table 1, both models have the same MSE in test 1 while the accuracy of neural network is lower than ANFIS. This implies that neural network has a weaker performance in predicting the category of patients with urgent conditions compared to ANFIS and this has reduced its accuracy. In test 2, both models show an acceptable performance in this group. The only difference is that ANFIS has a lower prediction error. The results of test 1 and test 3 reveals noticeable information. The prediction error of neural network is lower in test 1 but in test 3 its accuracy has also been reduced. The reason is that in test 1 neural network has predicted a large number of category 1 patients (urgent) as category 2 patients (emergent). This has raised its type II error which, in turn, has decreased its accuracy. In test 3, the neural network has predicted a large number of category 2 patients as category 1 patients. This has raised its type I error and, in turn, has raised its accuracy compared with test 1. Table 2 shows the results of sensitivity analyses in both models.

Table 2. sensitivity analyses of models

TEST(3)				TEST(2)				TEST(1)				Group
Specificity		Sensitivity		Specificity		Sensitivity		Specificity		Sensitivity		
NN	ANFIS	NN	ANFIS	NN	ANFIS	NN	ANFIS	NN	ANFIS	NN	ANFIS	
1	1	1	1	1	1	0.981	1	0.9	0.91	0.4	0.84	1
0.71	0.89	1	1	1	1	0.97	0.984	0.99	0.913	0.95	0.86	2
0.96	1	1	1	1	1	1	1	-	-	-	-	3
1	1	1	1	1	1	1	1	-	-	-	-	4

The values of the table have been derived from the following relations Kalhori (2011):

$$1) \text{ Sensitivity} = \frac{TP}{TP+FN}$$

$$2) \text{ Specificity} = \frac{TN}{TN+FP}$$

Where,

TP stands for emergent category predicted as emergent category.

TN stands for non-emergent category predicted as non-emergent category.

FN stands for emergent category not predicted as emergent category.

FP stands for non-emergent category predicted as emergent category.

Figure 3 shows Receiver Operating Characteristic (ROC) curves of the tests.

Figure 3: ROC curves of the tests

According to table 2 and figure 3, the lower accuracy of neural network in test 1 is due to its weak performance in predicting category 1 patients. It predicted many patients of category 1 as the patients of category 2. This has decreased its sensitivity and ROC curve to 0.4 and 0.709, respectively in category 1. In contrast, ANFIS has lower mistakes compared to neural network but it has a weaker performance in predicting the patients of category 2 compared to neural network. According to the results of both tests 2 and 3, it can be argued that ANFIS has a better performance than neural network. It also proves that ANFIS works better than neural network when less input is introduced to the system.

5. Conclusion

According to UNICEF reports, globally, road traffic injuries are the second leading cause of death for young people aged 5–25 years (UNICEF, 2014). Traffic accidents are a major problem in Iran. They restrict economic development and

threaten Iranian health and security. UNICEF reports show that in Iran road traffic accidents kill nearly 28,000 people and injure or disable 300,000 more each year. Every 19 minutes one person dies on Iran's roads and every two minutes a person survives a crash but with serious injury and perhaps lifelong disability (UNICEF, 2014). Consequently, a large number of injured people are referred to hospitals at the same time every day while it is impossible to provide care for all of them at once due to limited resources. Therefore, patients need to be categorized by the triage unit of hospitals. This is a newly-established unit in Iranian hospitals and all functions are performed manually based on the experience of the triage unit nurses. There is no computerized system to categorize patients and to accelerate the triage process.

This paper has designed a triage system by comparing the performance of ANFIS and neural network models. Both models have been trained by 3015 data from the data set containing different conditions of patients developed by the experts in the field and then tested by 417 data. Results show weaker performance of neural network in real data (test1) and in untrained data (test3) compared to ANFIS model. This implies that although neural network has a higher capability in learning, training and adoption, this is generally limited to the trained data and it shows a weaker performance in untrained data. Also, according to the tests conducted, ANFIS shows a better performance with fewer inputs compared to neural network.

However, it should be noted that Azeez et al (2013) showed that neural network with an accuracy of 99% had a better performance than ANFIS with an accuracy of 96%. This difference could be attributed to the selection process of their assessment system as well as the type of the collected data. It also showed that neural network performance was better than ANFIS when more inputs were introduced to the system.

According to performed assessments and based on the selected triage assessment method used for categorizing patients, this paper shows that ANFIS with an average accuracy of 96% has a better performance than neural network with an average accuracy of 92%. This implies that the use of combined systems is a better technique for increasing accuracy and decreasing prediction error as they could benefit from each other's advantages. In ANFIS, neural network with their higher learning, training and adoption capability cover the weakness of fuzzy system in training and adopting with environment. However, fuzzy system can provide information within if-then fuzzy rules and reduce the weakness of neural network in effective modeling of a human or an expert in a given field. In fact, it helps neural network to show a better performance when confronted with untrained data. Golding et al (2008) used a combination of fuzzy-Q learning and genetic algorithm to design a triage system. They concluded that if a combined triage system was used in hospitals, patients waiting times for prioritizing could be reduced by 48 minutes.

This paper shows the extent to which the use of such combined systems can be beneficial for rescue teams in categorizing emergency patients. According to the results of this study, the use of hybrid systems such as ANFIS in the hospitals triage units would allow doctors and nurses to just enter the patient's vital signs in the system, determine the patient's category and transfer them to the appropriate unit straightaway. Implementation of such a system, with the help of experts, in Iranian hospitals or any other countries that don't have a computerized system for triaging patients could be very beneficial and time saving.

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