DESIGN OF THE ARTIFICIAL NEURAL NETWORK MODEL FOR THE PREDICTION OF OUTCOME AFTER STROKE

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Abstract: In our contemporary research we are trying to develop the artificial neural network (ANN) model for the prediction of outcome after the occurrence of stroke. This paper mentions some important facts about stroke as well as the urgent need for Computer Assisted Decision Support (CAMS) systems in the relation to clinical practice. The short review of related studies of ANN in medicine is included. The model input and output parameters were selected and are also described. The basic ANN design for the predictive model is mentioned together with the future directions of our research.

1 OVERVIEW

Computer Assisted Decision Support (CADS) in medicine should enhance the consistency of medical care in the future. Today there is an expanding range of medical information stored in electronic form for each patient, which could be effectively used in computer-assisted diagnoses systems or preventive and predictive models. CADS systems are also excellent tools to cover rare conditions, since no clinical expert can be expected to possess encyclopedic knowledge of all of the exceptional manifestations of diseases.

In our proposed work we tried to set up a new predictive biomedical model which could be able to make a prediction of stroke outcomes from the analysis of various medical input parameters acquired after patient´s hospitalization. Our biomedical model uses the Artificial Neural Networks (ANN) as a new technology for CADS systems. Neural networks are very universal instrument of approaching problems. The results could be used for performing prediction if the output of the network is continuous or classification if the outputs are discrete values.

2 STROKE

Stroke is the third leading cause of morbidity and mortality in the Western world, following ischemic heart disease and cancer. There are more than 50 million stroke and transient ischemic attack (TIA) survivors all over the world. More than 1 in 5 survivors may have a subsequent stroke in the next 5 years. The worldwide economic cost of stroke including direct as well as indirect costs could be approximately \$68.9 billion. Permanent disability remains a big problem, between 15% and 30% of stroke survivors suffer permanent disability, 20% of victims require institutional care within 3 months after the stroke event (Lloyd-Jones et al., 2009).

One third of stroke patients are under the age of 65 that means a variety of populations are at the risk and the disease should no longer be considered confined to the elderly. Women are at a greater risk for stroke than men. In 2005, women accounted for 60.6% of stroke deaths in the US. The increased lifespan is the main factor for the increase in stroke occurrence. However there are many others medical risk factors including myocardial infarction, coagulopathies, peripheral vascular disease, hypertension, atrial fibrillation, or diabetes mellitus.

2.1 Classification of Stroke

The main stroke pathophysiological entites include thrombosis, embolism, and hemorrhage. Stroke can be classified as ischemic or hemorrhagic types, with ischemic stroke accounting for approximately 85% of the total number. Ischemic stroke occurs due to

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either intracranial thrombosis or extracranial embolism. Intracranial thrombosis is joined to atherosclerosis, whereas extracranial embolisms arise from the extracranial arteries or from the myocardium, often because of concurrent myocardial infarction, mitral stenosis, endocarditis, atrial fibrillation or congestive heart failure. The classification of hemorrhagic stroke can be done as either intracerebral hemorrhage (ICH) or subarachnoid hemorrhage (SAH). The common causes for both ICH and SAH contain hypertension, trauma, drug use, or vascular malformations (Adams et al., 1993, Lloyd-Jones et al., 2009). In our case the TOAST (Trial of Org 10172 in Acute Stroke Treatment) classification of subtypes of acute ischemic stroke is used. The acute ischemic stroke subtypes than include Large-artery atherosclerosis (embolus/thrombosis), Small-vessel occlusion (lacune), Stroke of other determined etiology and Stroke of undetermined etiology. The hemorrhagic stroke type is also included in the model.

2.2 Clinical Diagnosis of Stroke

Stroke is a medical emergency. The successful treatment relies especially on its right and well-timed clinical diagnosis. Great effort in acute stroke management is focused on correct and rapid diagnosis and maximal shortening of “onset to needle time”. It is critical for determining eligibility for thrombolytic therapy, as the window of opportunity for therapeutic effectiveness of stroke is only a few hours (Morgenstern et al., 2004).

There are many new imaging techniques available which leads to the potential for earlier opportunities for therapeutic intervention in stroke patients. The neurological imaging can be used for the differentiation between hemorrhagic and ischemic stroke. Important features gained from brain imaging include detecting early infarction and determining the location and degrees of infarct and vascular distribution of the lesions. Computed tomography (CT) is routinely used in the initial acute assessment of stroke patient. In acute stroke case, MRI diffusion-weighted imaging (DWI) techniques have the ability to differentiate between various stroke subgroups.

2.3 Therapeutic Intervention in Stroke

The main goal in stroke therapeutic intervention is to salvage as much cerebral tissue as possible. Therefore effective thrombolytic therapy must be initiated rapidly. In 1996, US Food and Drug Administration (FDA) approved revolutionary therapeutic intervention with intravenous recombinant tissue plasminogen activator (rtPA). It has been used consistently for thrombolysis in acute stroke. The window of opportunity is less than 4.5 h from the onset of symptoms (Hacke et al., 2008).

3 ARTIFICIAL NEURAL NETWORKS IN MEDICINE

The neural networks application in the diagnosis of cardiovascular disease, primarily in the detection and classification of at-risk people from their ECG waveforms was done (Nazeran and Behbehani, 2001). Anoher study uses neural networks to classify normal and abnormal ECG waveforms and the abnormal ECG and is described in (Celler and Chazal, 1998). It made classification of the waveforms with 70.9% accuracy.

In the next study the ANN which uses non-linear statistics for pattern recognition was used in predicting one-year liver disease-related mortality with the initial clinical evaluation information.The application of ARTMAP in medicine include classification of cardiac arrhythmias was described in (Ham and Han, 1996). The selection of treatment for schizophrenic and unipolar depressed in-patients was also made (Modai et al., 1996). Another study described using of ANN to predict patients with colorectal cancer more accurately than clinicopathological methods.

Anothe work based on ANNs is able to detect ischaemic episodes in long duration ECG recordings (Papaloukas et al., 2002). The use of the ANN model as a data mining tool was made to model complex behaviour of different molecular markers of dialysis treatment (Elmer et al., 2005). The ANN model was also used for prediction of tromboembolic stroke (Shanthi et al., 2010).

4 THE PROPOSED MODEL

The main goal of our proposed system should be the correct prediction of the stroke outcomes in patients who were admitted to the hospital with the stroke diagnosis. The outcome prediction will be made from the various input medical data processed in the model. The output describes the overall medical condition of the stroke patient which is represented as a grade on some international summarizing scale. The model outputs (stroke outcomes prediction) are computed for the time points 7 and 90 days after the stroke occurrence (patient´s admittance to the hospital).

In the proposed model design we use two different international scale systems for the stroke. First is the 42-point National Institutes of Health Stroke Survey (NIHSS) scale. It was developed to assist with diagnostic consistency among physicians and was designed to be completed within 5 to 8 min (Goldstein and Samsa, 1997). The NIHSS quantifies neurological deficits in stroke patients. The second one is The Modified Rankin Scale (mRS). It is a commonly used scale for measuring the degree of disability or dependence in the daily activities of people who had a stroke. This scale is widely used in clinical outcome measures for stroke clinical trials. The scale are from 0-6, running from perfect health without symptoms to death (0 - no symptoms, 1 - no significant disability, able to carry out all usual activities, despite some symptoms, 2 - slight disability, able to look after own affairs without assistance, but unable to carry out all previous activities, 3 - moderate disability, requires some help, but able to walk unassisted, 4 - moderately severe disability, unable to attend to own bodily needs without assistance, and unable to walk unassisted, 5 - severe disability, requires constant nursing care and attention, bedridden, incontinent, 6 – dead).

4.1 Patient Data and Feature Selection

The various medical inputs for our model were selected with the help of neurological experts from the department of neurology, Charles University Medical School and University Hospital in Plzen. All stroke patient´s data either for the training set or the validation set of the model will come from the University Hospital in Plzen.

The input parameters of the model are listed in the table 1 (SITS Parameters) and table 2 (non-SITS parameters). SITS (Safe Implementation of Treatments in Stroke) is an academic-driven, non-profit, international collaboration. It is an initiative by the medical profession to accelerate clinical trials and to certify excellence in acute and secondary prevention stroke treatment and to develop knowledge and leading research. The SITS Network includes a broad range of hospitals, as well as the University Hospital in Plzen. The SITS Stroke Registry is an internet-based interactive stroke registry developed by SITS. It serves as an instument for stroke centres to compare own treatment results with other stroke centres. The basic parameters which can be found in SITS protocols were enriched with some other inputs, such as new laboratory markers of acute stroke or stroke type classification. This expert´s medical input analysis and selection of model parameters should ensure superior predictive accuracy of our biomedical model.

Table 1: SITS input parameters.

SITS Parameters		
In. No.	**Input Name**	**Input range**
Modified Rankin Scale before stroke		
1	mRS score	0 – 6
Prior treatments		
2	Antiplatelet tr. (Dypiridamol, Clopidogrel)	Yes/No
3	Anticolagulants (Heparin)	Yes/No
4	Anti – diabetic (Insulin) tr.	Yes/No
5	Antihypertensive tr.	Yes/No
Risk factors		
6	Hypertension	Yes/No
7	Diabetes (Dg. of diabetes)	Yes/No
8	Hyperlipidemia (Dg.of hyperlipidemia)	Yes/No
9	Current Smoker	Yes/No
10	Previous Smoker	Yes/No
11	Previous Stroke (earlier than 3 months)	Yes/No
12	Previous Stroke (within 3 months)	Yes/No
13	Previous TIA / Amaurosis fugax	Yes/No
14	Atrial fibrillation	Yes/No
15	Congestive heart failure	Yes/No
Laboratory Indicators		
16	Glucose (mmol/l)	Number
17	Cholesterol (mmol/l)	Number
NIHS		
18	NIH Score	0 – 42
Imaging – CT		
19	CT current infarct	Yes/No
20	Local haemorrhage	Yes/No
Other Parameters		
21	Age	Number
22	Sex	M / F
23	Weight	Number
24	Systolic blood pressure (mmHg)	Number
25	Diastolic blood pressure (mmHg)	Number

5 THE ARCHITECTURE OF ANN

The architecture of the artificial neural network is the multilayered feed-forward network with 37 input nodes (in the future 41). The first experimental case uses 20 hidden nodes. The output is designed as one node which could be able to calculate the overall patient’s stroke outcome in the international scale of NIHSS and RANKIN.

Table 2: Non-SITS input parameters.

Non SITS parameters		
In. No.	**Input Name**	**Input range**
Treatment		
26	I.V. Trombolysis	Yes/No
27	Stroke care unit	Yes/No
Stroke Type		
28	Large-artery atherosclerosis	Yes/No
29	Cardioembolism	Yes/No
30	Small-vessel occlusion	Yes/No
31	Stroke of other determined etiology	Yes/No
32	Haemorrhalgic stroke	Yes/No
Laboratory indicators		
33	CRP	Number
34	Platelets	Number
35	Leukocytes	Number
36	Fibrinogen	Number
37	Vitamin D	Number
Other possible laboratory indicators (in the future)		
38,39,40,41	IL 6, SAA, NSE, PARK 7	Number

6 CONCLUSIONS

In this paper we have discussed a design of our new biomedical model for the stroke outcome prediction which is based on artificial neural network architecture. First important part of the model creation was the selection of input and output parameters. This task was done with the help of neurological experts from the University Hospital in Plzen. Than the architecture of an ANN was designed and also briefly referred in this paper. Now the model is prepared for training patient´s data set. The ANN training and optimization of the model are our main research tasks to the future. The work presented in this paper is supported by The Czech Science Foundation project 106/09/0740 dealing with brain perfusion modelling.

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