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Blood clotting prediction model using Artificial Neural Networks and Sensor Networks

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Abstract

The purpose of the given paper is to analyze blood clots (BCs) by using Artificial Neural Network (ANN) using the physical symptoms as the input data. Such a NN provides an analytical alternative to conventional techniques, and allows the user to model BCs. Sensor Data *application provides direct access to data. All the data have been collected by using different types of sensors. Based on the symptoms these sensors can pass the data (offline or in real time) to the NN, where the latter will analyze it though a modelling system designed to distinguish the blood clotting. This paper illustrates the effect of using a combination of different types of sensors. These sensors will provide inputs to a well-designed NN that aims to model the BC, and analyse it in a way that gives better predictions of the presence of a BC or at least an early warning indicating BC presence. By using this model, developed in the given paper, the patients will be able to predefine danger of occurrence of blood clotting.*

***Keywords**: artificial neural network model, blood clotting prediction, sensor measurement.*

1. Introduction

Brain is the control center of the body. It controls thoughts, memory, speech and movement. It regulates the function of many organs. When the brain is healthy, it works efficiently and automatically. However, when disorders occur, the results can be devastating. One of the common disorder of brain is stroke also called brain attack (a medical emergency). Stroke is a major cause of death and disability in both the developed and the less developed countries [1] [2].Stroke consumes an important part of the total healthcare costs (i.e. excluding social care and indirect costs) in Europe and USA [3].

The World Health Organization reports that 15 million people worldwide suffer stroke; and of these, 5 million die and a further 5 million are left permanently disabled, many severely impaired. Consequently stroke is a major cause of mortality world-wide. Most strokes are caused by a blood clot that occludes an artery in the cerebral circulation. Thrombolytic agents such as Alteplase are used to dissolve blood clots that arise in the cerebral arteries of the brain but there are limitations on their use. Recently screening for patients at risk of strokes and TIA’s has come into being. If such plaques are detected in the carotid arteries (by Ultrasound), a Carotid endarterectomy (CEA) - a surgical operation - may be performed to remove the occlusive plaque.

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Blood clots form as a result of the coagulation of blood. A blood clot that forms in a vessel or the heart and stays in the location it formed is called a thrombus. A blood clot that leaves the area of its formation is known as an embolus/embolism (disorder). Thrombi or emboli may attach to a blood vessel and partially or completely block the flow of blood in that vessel. Blockage that prevents normal blood flow and proper intake of oxygen is referred to as ischemia. If not treated quickly, damage or death (infarction or necrosis) of the tissues in that area occurs [4-6]. One of the most common forms of blood clot disorders is deep venous thrombosis. It is speculated that there are approximately 3 million cases per year in the United States [4-6]. While not necessarily a reliable number, this still indicates that blood clot disorders occur in a very large portion of the US population each year.

There are a diverse range of diagnostic techniques available to physicians when a blood clot is suspected. These include but are not limited to duplex ultrasound, magnetic resonance imaging, venography, computed tomography scans, magnetic resonance angiography, D-Dimer test, arteriography/angiography, and impedance plethysmography. These techniques differ in the method they employ to determine the existence of a blood clot, and are also designed specifically to detect different disorders.

Early detection of blood clots was studied using neural network models [8 -11, 12-14], statistical models [15, 16, 17], genetic algorithms [18], and other machine learning techniques including decision tree, fuzzy sets, and evolutionary algorithms. The models used on practical study of patients, for the early diagnosis of myocardial infarction, chest pain, heart attack, develop the statistical models on available data, and on available practical issues associated with the realization of a cardiac functions. Most of the information on Web available are the physical symptoms for blood clots. But none of these symptoms are used to make a tool useful for the average citizen. For every suspected case, doctors run a number of tests and spend enormous amounts of money before they ascertain the real cause. We feel a simple device developed as an outcome of the research to predict the symptoms of blood clot will help many people to avoid the deaths happening today. The current research is based on developing an inexpensive tool to detect blood clots in patients suffering from headache and other symptoms.

Over the past decade, other methods of treatment have been developed which include Thrombectomy Devices e.g. the 'GP' Thrombus Aspiration Device GPTAD - fig. 1) [19]. Such devices have the potential to be used as an alternative to thrombolytic agents or in conjunction with them to extract clots in different arteries e.g. in the middle cerebral artery of the brain, carotid, popliteal artery, etc. A clot of blood may also become attached to the plaque (deposition of fats and lipids that may arise within arteries) in a distal artery, and subsequently become detached and travel to the cerebral circulation giving rise to a stroke. In the case of 100% occlusion, it causes total blockage of the artery.

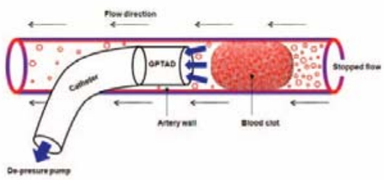

Figure 1. Representation of the GPTAD sited in the artery

Some catheter diameters and distances between the GPTAD device and the blood clot are compared for a 95% occlusion to highlight differences between these situations. This level of occlusion has been selected since many thrombosis that occur in arteries exhibit this high level of occlusion by blood clots. In cases with a low occlusion, the GPTAD would not be useful, since blood would be sucked principally instead of extracting the clot.

2. Neural Network description

One type of network sees the nodes as ‘artificial neurons’. These are called artificial neural networks (ANNs). An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through *synapses* located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain *threshold*), the neuron is *activated* and emits a signal though the *axon*. This signal might be sent to another synapse, and might activate other neurons.

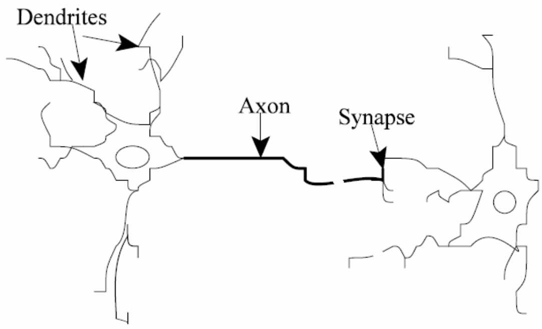

Figure 1. Natural neurons

Neural networks (NN) are inspired by nervous systems found in biological organisms. A neural network is designed to capture relationships among dependent and independent variables in a given sample data set. Unlike parametric models used in statistical techniques, ANN does not require any restrictive a priori assumptions about the relationship among independent and dependent variables [6]. In addition, they are adaptive and can respond to structural changes in the data generation process in ways that parametric models cannot. An ANN consists of a number of connected nodes each of which is capable of responding to input signals with an output signal in a predefined way. These nodes are ordered in layers. A network consists of one input layer, one output layer, and an arbitrary number of hidden layers in between.

The backpropagation algorithm (Rumelhart and McClelland, 1986) is used in

layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals “forward”, and then the errors are propagated backwards. The network receives inputs by neurons in the *input layer*, and the output of the network is given by the neurons on an *output layer*. There may be one or more intermediate *hidden layers*.

The backpropagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the backpropagation algorithm is to reduce this error, until the ANN *learns* the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.

The activation function of the artificial neurons in ANNs implementing the backpropagation algorithm is a weighted sum (the sum of the inputs x_i multiplied by their respective weights w_{ji}) :

$$A_j(\bar{X}, \bar{W}) = \sum_{i=0}^{n} X_i W_{ji} \quad (1)$$

All connections are assigned a weight (a real number). The training or learning of the network occurs through the introduction of cycles of data patterns (epochs or iterations) to the network. One problem with neural network training is the tendency of the network to memorize the training data after an extended learning phase. If the network over learns the training data it is more difficult for the network to generalize to a data set that was not seen by the network during training.

Therefore, it is common practice to divide the data set into a learning data set that is used to train the network and a validation data set that is used to test network performance.

In medical practice, ANNs are generally used to diagnose and monitor the prognosis of a disease. ANNs have been used to determine prognosis in trauma, prognosis after cardiopulmonary resuscitation, outcome of treatment for ovarian cancer, prognosis in acquired immunodeficiency syndrome (AIDS), predicting mortality of patients with endstage liver disease, prognosis for patients with colonic cancer, detecting extensive coronary artery disease, predicting length of stay in the intensive care unit following cardiac surgery and predicting the risk of death for small-cell lung cancer patients.

3. Model of the Neural Network for blood clots

The model created in this paper is a BP neural network model with 10 inputs which are combination of symptoms and risk factors of blood clots provided by the patients.The presence of symptom and risk factor is 1 and absence is 0.In this model single hidden layer has been used. Output layer consists of one node whichrepresents the probability of occurrence of blood clots.

3.1 Input layer

The input layer of a neural network is determined from the characteristics of the application input. For prognosis of blood clotting we used 10 inputs which are combination of symptoms and risks factors. Following symptoms and risk factors are the input to the neural network:

S1 Sudden numbness or weakness of face, arm or leg, often one side of the body.
S2 Sudden confusion, trouble speaking or understanding.
S3 Sudden trouble seeing in one or both eyes.
S4 Sudden trouble walking, dizziness loss of balance or coordination.
S5 Sudden severe headache with no known cause.
R6 High blood pressure
R7 Diabetes
R8 Transitory ischemic attack
R9 Stenos carotid artery
R10 Smoking

3.2 Hidden layer

Hidden layer automatically extracts the features of the input and reduces its dimensionality further [6]. There is no specific rule that dictates the number of hidden layers. Usually, one hidden layer is used. The reason for this is that one hidden layer is sufficient to approximate any continuous function to an arbitrary precision. In this model we chose one hidden layer with 20 neurons & logistic sigmoid functions.

3.3 Output Layer

We can predict the presence or absent of blood clots based on the output of the neural network. So if output is 1 blood clotting is present & if it is 0 blood cloting is absent. We assume that the actual output of the neuron in the output layer is yj(t) at time t and the expected output dj(t), so the network error function E(t) at the time t will be defined as follows: q is the number of neurons in the output layer and is one for this neural network; ε is a pre-set error margin.

$$E(t) = \frac{1}{2}\sum_{j=1}^{q}(y_j(t) - d_j(t))^2 \tag{20}$$

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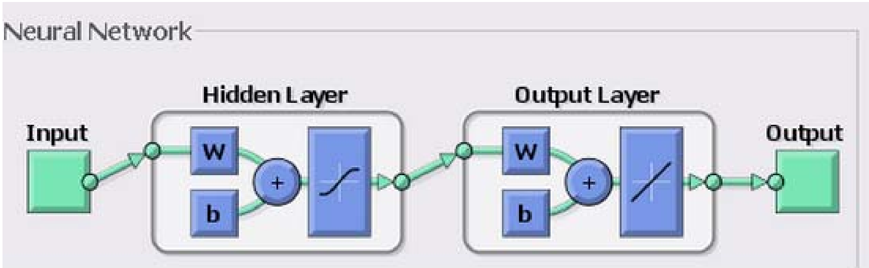

Fig.1 Neural Network Model (nftool)

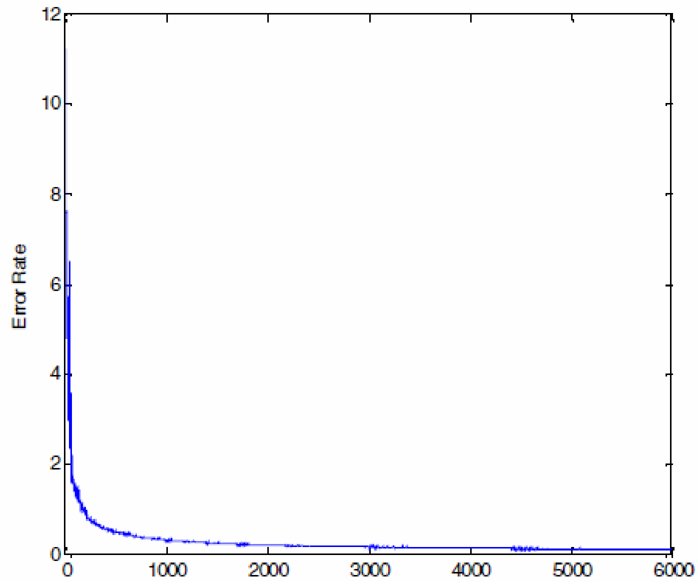

Fig. 2 Training for Blood clots with 214 samples

4. Sensor Measurement

Sensor Data application provides direct access to data. All the data have been collected by using different types of sensors. Based on the symptoms these sensors can pass the data (offline or in real time) to the NN, where the latter will analyze it though a modelling system designed to distinguish the blood clotting. The method based on magnetoelastic sensors has been used for the monitoring of blood coagulation. The ribbon-like magnetoelastic sensor oscillates at a fundamental frequency, which shifts linearly in response to applied mass loads or a fixed mass load of changing elasticity. The magnetoelastic sensors emit magnetic flux, which can be detected by a remotely located pick-up coil, so that no direct physical connections are required. During blood coagulation, the viscosity of blood changes due to the formation of a soft fibrin clot.

5. Conclusion

In the given paper, ANN based model has been used to develop a system in which patients would be able to self-diagnose themselves Before visiting a doctor. Prognosis of early diagnosis of blood clots with ANN models has the best performance in large data sets. MATLAB program was

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developed to model and train NN. The 'nftool' were used to diagnose the symptoms. The 'nftool' proved to be the most effective due to its higher percent correlation.

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