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## Neural Networks In Medical And Healthcare

**S. Senthil Kumar**

Research Scholar, Department Of Computer Science  
Dr. SNS Rajalakshmi College Of Arts And Science, Coimbatore, Tamil Nadu, India

**Dr. K. Ananda Kumar**

Assistant Professor, Department of Computer Applications  
Bannari Amman Institute of Technology, Coimbatore, Tamil Nadu, India

### **Abstract:**

Neural networks provide significant benefits in medical research. They are actively being used for such applications as locating previously undetected patterns in mountains of research data, controlling medical devices based on biofeedback, and detecting characteristics in medical imagery. In its first part, this contribution reviews shortly the application of neural network methods to medical problems and characterizes its advantages and problems in the context of the medical background. Artificial neural networks are computational paradigms based on mathematical models that unlike traditional computing have a structure and operation that resembles that of the mammal brain. Neural networks lack centralized control in the classical sense, since all the interconnected processing elements change or “adapt” simultaneously with the flow of information and adaptive rules.

One of the original aims of artificial neural networks (ANN) was to understand and shape the functional characteristics and computational properties of the brain when it performs cognitive processes such as sensorial perception, concept categorization, concept association and learning. However, today a great deal of effort is focused on the development of neural networks for applications such as pattern recognition and classification, data compression and optimization.

**Key words:** neural network, artificial intelligence, medical diagnosis, signal processing, classification

### **1.Introduction To Neural Networks**

Neural networks can be applied to medicine in four basic fields: modelling, bioelectric signal processing, diagnosing and prognostics

- Modelling: Simulating and modelling the functions of the brain and neurosensory organs.
- Signal processing: Bioelectric signal filtering and evaluation
- System control and checking: Intelligent artificial machine control and checking based on responses of biological or technical systems given to any signals
- Classification: Interpretation of physical and instrumental findings to achieve a more accurate diagnosis
- Prediction: Neural network provides prognostic information based on retrospective parameter analysis

*Table 1:Functional Division Of Neural-Network Applications*

Artificial neural networks provide a powerful tool to help doctors to analyse, model and make sense of complex clinical data across a broad range of medical applications. Most applications of artificial neural networks to medicine are classification problems; that is, the task is on the basis of the measured features to assign the patient to one of a small set of classes.

### **2.Artificial Neural Networks**

An artificial neural network (ANN) is a computational model that attempts to account for the parallel nature of the human brain. A (ANN) is a network of highly interconnecting processing elements (neurons) operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. A subgroup of processing element is called a layer in the network. The first layer is the input layer and the last layer is the output layer. Between the input and output layer, there may be additional layer(s) of units, called hidden layer(s).

In this paper, after describing the basic elements of neural networks and sketching their operation, we discuss the main application fields of neural network technology in medicine.

### 3.Application In The Medicine

An overview of the main disciplines is cited here:

#### 3.1.Cardiology

Serum enzyme level analysis forms the basis of acute myocardial infarction (AMI) diagnostics. A neural network has been trained in the analysis of these heart enzyme levels. Diagnostic accuracy proved to be 100% with an 8% false positive rate. Later, the same research group developed an integrated decision support system in which a neural network was trained not only by enzymatic data, but also by EKG-phenomena, subjective symptoms and changes after administration of nitroglycerin.

Neural networks were used by Farruggia et al. to study the sophisticated control of cardioverter defibrillators. Neural networks have been used to model heart rate regulation while Ortiz et al. used them to examine heart failure.

#### 3.2.Analysis Of ECGs (Electrocardiogram)

Computational ECG-analysers are widely used in clinical practice. Currently available systems are based on mostly rule-based mathematical and statistical algorithms for the analysis of ECG-signals. There are several attempts to use neural networks to improve the diagnostic accuracy and achieve more faultless operation even in the presence of complicating factors. Evaluation of long term ECG recordings (Holter-monitor) requires automated recognition of events that occur infrequently; human evaluation of nearly 90.000 ECG-complexes a day is a time consuming and exhausting procedure. An adequately trained neural network can recognize given disorders with up to 99.99% sensitivity.

#### 3.3.Intensive Care

The evaluation of clinical parameters and especially the use of alarm signals in an intensive care unit is currently done on a one by one basis. An alarm system that is able to evaluate changes and interactions of physical, chemical and thermodynamical parameters simultaneously would be most ideal. Conventional technology would have to assume a full knowledge of the clinical relationship for such a system. Because these relations are only incompletely known, the neural network's ability for learning and adaptation could be expected to be utilized. In anesthetic practice, physicians are required to monitor more and more displays and evaluate an increasing number of signals. Processing of this amount of data requires experienced and skilled clinicians to ensure intelligent, high-level systematization and timely evaluation of their input. Neural networks can definitely support physicians by initiating necessary responses in case of emergency (within 17 seconds instead of the 45 seconds average by clinicians).

#### 3.4.Gastroenterology

Determination of the prognosis of patients undergoing hepatectomy is an overlapping field of gastroenterology and oncology. Hamamoto et al. Trained a back propagation neural network with clinical findings of 54 patients; data of 11 patients were used for testing. The prognosis in the test patients was reproduced with 100% accuracy.

#### 3.5.Pulmonology

Pulmonologists and radiologists have worked together on the development of a system for the classification of solitary pulmonary nodules. According to their results, neural network analysis of such disorders was less successful than conventional classification methods. In contrast, neural networks were more accurate than 2 well-trained experts in the diagnosis of pulmonary embolism in 1064 patients.

#### 3.6.Oncology

There are several systems available for the diagnosis and selection of therapeutic strategies in breast cancer. A neural network judged the possible recurrence rate of tumors correctly in 960 of 1008 cases by using data from lymphatic node positive patients (tumor size, number of palpable lymphatic nodules, tumor hormone receptor status, etc.). Baker et al. Reported that they came to similar results by neural network evaluation of the parameters of the BI-RADS standardized code system. Fogel stated in his paper on neural network recognition of breast cancer that evaluation of mammographic, cytological and epidemiological findings in an integrated system is thought to be useful in the diagnostic process.

#### 3.7.Neurology

The sometimes difficult differential diagnosis between Alzheimer disease and vascular dementia can be assisted by neural network analysis of brain SPECT image data. An 86% sensitivity rate was achieved in one study. Guigo et al. studied and modeled the learning process of the prefrontal cortex. This theoretical study could promote development of more complex artificial neural network structures.

#### 3.8.EEG (Electroencephalogram) Analysis

Several neurological disorders are routinely examined by EEG analysis. Differentiation between physiological and pathological alterations requires the flexibility and excellent adaptation capability of neural networks through the processing and recognition of huge amounts of various EEG-complexes. In a laboratory model, a back propagation neural

The network was trained to recognize spontaneously occurring HVS-patterns (High Voltage spike-and wave Spindle) in rats. This well-trained and optimized network could detect the presence of HVS in EEGs recorded for 12 night hours with 93-99% sensitivity. However, falsely detected events (non-HVS, artefacts) varied over a wide range (18-40%). This attempt does, however, demonstrate the potential usefulness of neural networks in the recognition of EEG patterns and consequent construction of automated EEG evaluation systems for detection, observation and tracking of epileptiform patterns. Gabor et al. has reached a similar conclusion by identifying typical epileptiform alterations of the EEG in an epileptic seizure. There are several neural network classifiers that derive data from the EEG by data pre-processing. Examining the capability to classify sleep stages in infants using artificial neural networks, Pfurtscheller et al. reported a 65-80% accuracy in the classification of EEG patterns into 6 classes. In Boston, EOG (electrooculogram) and EMG (electromyogram) data in addition to EEG patterns were used for neural network training to study sleep stages. The investigators achieved a remarkable accuracy of 93.3%.

### *3.9. Otorhinolaryngology*

Neural networks have proven to be a new and effective method for modelling hearing. This technique could become useful for understanding, modelling and treating speech and hearing impairments. Hearing-aids can well be improved by using neural networks for noise filtering and optimization of parameter settings.

### *3.10. Obstetrics And Gynecology*

Benesova et al. used neural networks to determine the teratogenicity of perinatal administered drugs. Lapeer and his group applied neural networks for similar predictive tasks, attempting to pick out perinatal parameters influencing birthweight.

### *3.11. Ophthalmology*

Maeda et al. applied neural networks to videokeratography pattern interpretation in the diagnosis of shape abnormalities of the cornea that relate to several abnormalities. Cornea maps were divided into a training set and a test set. The network achieved correct classification for all the maps in the training set, and an 80% rate for the test set. Slightly better results were observed in automated visual field diagnosis using neural network analysis.

### *3.12. Radiology*

To date, the application of neural networks seems to be most interesting and most powerful in the field of radiology. Images contain much information and they are so complicated that it's all but impossible to interpret them using conventional rule based systems. By selecting an appropriate training set and learning process, neural network modeling becomes suitable for noise filtering and for recognition of unusual images. For cold lesion detection and localization in SPECT images a neural network was trained using images with different sizes and noise levels. The network scanned the whole image and recognized alterations with a high sensitivity, and with only a few false-positive errors. Another specific application uses a back propagation algorithm for the detection of 7 coronary artery disorders on the basis of myocardial SPECT images. A neural network has also been applied for the detection of microcalcification on digital mammograms. The program is able to locate regions of interest and differentiate pathological alterations from false-positive ones. Conventional image analysis systems process information row by row. However, newer decision supporting systems use parameters derived from the image by pre-processing. These parameters are obtained from the features of the image. Abdominal ultrasound and laboratory investigations do not usually provide enough data for the differentiation of liver diseases. Based on ultrasonographic and laboratory findings, a neural network was created to diagnose five classes of liver diseases. The network achieved a recognition accuracy somewhere between the results of residents and those of certified radiologists. Prateret al. reported similar results with ultrasonographic examination of the prostate. In another study, experienced radiologists designed a database classifying 14 features of mammographic images. A back propagation neural network trained by this database achieved a higher classification accuracy than the experienced radiologists. There is also a neural network available for the interpretation of breast cancer ultrasonographic images. Data for the training for this network was also obtained by feature extraction pre-processing.

### *3.13. Pathology*

Dawson et al. created a neural network to establish the grading of breast carcinoma. They examined features extracted from light microscopic images. A similar technique used to differentiate tubular carcinoma from sclerosing adenosis seems also to be useful. According to Wolberg et al. routine diagnosis of breast cancer can be aided by neural networks. Kolles created a system for grading astrocytomas based on immunohistochemically and DNA stained microscopic images. Even prostate cancer spread can be evaluated using neural networks. Analysis of DNA flow cytometric histograms by neural networks yields benefits in breast cancer screening and estimating risk. In a study reported from Australia, patients were divided into low risk and high risk groups. To increase diagnostic precision, neural network analysis was used in conjunction with conventional statistical rule-based techniques.

### *3.14. Cytology*

Perhaps the most widely-known application of neural networks in medicine is the PAPNET system. It is designed and used for automated cytological screening of cervical smears. Boon pointed out that the number of false-negative cases can be reduced using the PAPNET for revising negative cases. Brouwer's work confirms that malignant cervical cells can be recognised by neural networks.

In our own work, we compared the usefulness of linear discriminant analysis and back propagation neural networks for the evaluation of parameters that were obtained by quantitative morpho- and densitometric cytological examination of gastric imprint smears. According to our results neural networks yield slightly better results compared to traditional statistical techniques in the classification of normal, dysplastic and malignant cases.

### 3.15. Genetics

Errington and Graham trained a neural network for chromosome classification based on pre-processed data representing the shape, size and banding of chromosomes. They stated in an earlier publication that the classification accuracy of a neural network can be improved by redesigning the training set; however traditional algorithms must be redefined in the event of inaccurate operation. Burstein et al. designed a neural network model for studying the entire spatial and temporal embryogenesis and genetic pattern formation in *Drosophila*.

### 3.16. Clinical Chemistry

Intelligent evaluation of the results from clinical chemistry analysers and programmed answers for unexpected events has been the subject of several studies. Neural networks created the conditions for automatic result control and the subsequent need for further determinations. By automated evaluation of electrophoretic patterns, effectiveness and efficiency is increased.

### 3.17. Biochemistry

The ProCANS (Protein Classification Artificial Neural Networks) system has been designed for superfamily classification of proteins. Training was based on the official protein sequence database (Protein Identification Resource). The performance of the network on the Cray supercomputer was convincing: 90% classification accuracy and less than 0.1 seconds per sequence classification rate. The relationship of primary protein structure to the features of complex organisation is well-known. However, the laws of this mechanism are currently unknown. A simple back propagation neural network was trained based on the features and amino acid sequences of two types of oligopeptide chains each containing 130 amino acids. The study determined that neural networks are suitable for representation of amino acid sequence - structure relation.

## 4. Neural Networks: Artificial Intelligence In The Future?

As yet, neural networks have not broken through many of the barriers to applied sciences. This technique was been applied only for testing mathematical models developed for simple problem solution in practice. Application of neural networks must currently be supported by conventional mathematical methods. In this way, neural networks can result in more success in pattern recognition and classification compared to purely conventional techniques. To become more widespread, development of new models are required that are able to manage complicated and complex real-world problems.

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