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A Neural Network Based Detection of Brain Tumours Using Electroencephalography

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ABSTRACT
This paper presents pattern recognition of electroencephalograph (EEG) signals using artificial neural networks (ANNs). The ANN based EEG classifier in this paper distinguishes between the EEG signal of a normal patient and that of a brain tumour patient. A further exercise carried out is a comparison between the different size of input images and their results. Using artificial neural networks, the need for an expert neurologist to analyze EEG signals is eliminated or minimized. This will in turn benefit rural/country areas where there is a shortage of expert doctors for EEG analysis or medical professionals of screening EEG signals for abnormalities under the different noisy conditions in which the EEG signals are captured/analysed. The preliminary results are presented to show that an ANN can classify correctly EEG signals of healthy and brain-tumour patients.

KEYWORDS
Neural networks, brain tumours, EEG signals

1. Introduction

The organs and tissues of the body are made up of tiny building blocks called cells. Cancer is a disease of these cells. Although cells in different parts of the body may look and work differently, most repair themselves in the same way, by dividing to make more cells. Normally, this turnover takes place in an orderly and controlled manner. If, for some reason, the process gets out of control, the cells will continue to divide, developing into a lump, which is called a tumour, as shown in figure 1. Tumours can be benign or malignant. In a benign tumour, the cells do not spread to other parts of the body and therefore are not cancerous [1]. If they continue to grow at the original site, however, they may cause a problem by pressing on the surrounding organs. A malignant tumour consists of cancer cells, which have the ability to spread beyond the original site. Sometimes cells break away from the original (primary) cancer and spread to other organs in the bloodstream or lymphatic system. When these cells reach a new site they may go on dividing and form a new tumour, often referred to as a secondary or a metastasis.

There are numerous methods used to diagnose a brain tumour; these methods include a magnetic resonance imaging (MRI) scan, computerised axial tomography CAT (CT) scan, an angiogram, or an electroencephalogram, to name a few. MRI and CAT scans however have the disadvantage since the patient is exposed to a dose of radiation. With an electroencephalogram, the abnormalities in the brain functioning can be identified and if this is carried out at an early stage brain disorders can be treated preventing further complications.

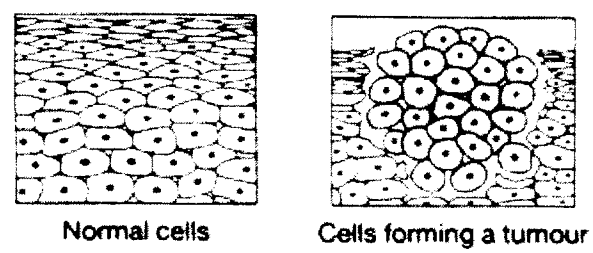

Figure 1: Formation of a tumour

Artificial neural networks have been applied to many computer vision tasks within an engineering context. Medical imaging processing is an area in which ANNs are widely employed in this manner [2]. Many modalities now exist for the acquisition of images for the use of in clinical medicine, such as MRI, CT, X-ray, Ultrasound, PET, and SPECT. These techniques are widely used which, although very powerful, is capable of producing dozens of images per patient. These routine production of vast quantities of medical images results in a very heavy work load being placed on medical professionals who have to screen these images for abnormalities. In order to alleviate some of this workload, a large amount of computer vision research has been target at automatic abnormality detection in medical images. With the EEG analysis, the artificial neural network is extremely useful in estimating functions that do not have explicit mathematical models since ANNs can often find hidden relationships in the wave signal data and detect abnormalities. ANN based EEG classification can lead to the development of a prototype system that performs a robust, target segmentation of EEG wave signals in order to automatically detect a specific abnormality.

This paper focuses on the use of artificial neural networks for detection of brain tumours by classifying EEG signals of healthy and brain tumour patients into normal and abnormal signals respectively. Section 2 describes the EEG signal in general and that of brain tumour patients. Section 3 describes artificial neural network based EEG classifier. Section 4 presents some preliminary results of an ANN based EEG classifier for patients with and without brain tumour, and the comparison results between different size of input samples.

2. Electroencephalographs

2.1 The Electroencephalograph

Electroencephalogram (EEG) is process of monitoring the brain activities for diagnosing and treating psychological disorders such as brain tumours, multiple personality disorders, and depression. The EEG equipment is used to record the electrical potentials generated by the nerve cells in the cerebral cortex [3]. These electrodes are carefully placed along the head at regular intervals to sense the electrical changes in the nerve cells once recording has begun. The original signals from the brain are very small (microvolts), and the EEG equipment amplifies the size of these electrical signals so that they can be plotted on a paper or stored in the computer for interpretation by a neurologist or EEG consultant. EEG analysis is not the only test carried out, investigation with other tests such as MEG, PET, and functional MRI, may be used to correctly interpret/validate the findings of the EEG analysis [4].

2.2 Pattern Recognition in EEG Waves

General situations cannot be assessed in terms of isolated facts. Rather, situations need to be described in terms of patterns on interrelated facts. Sometimes the interrelationship is practical, in the sense that all those facts pertain to the same object or situation. In other cases, a pattern may be meaningful only because of explicit relationships among the various features of the pattern. An EEG waveform is a wave of electricity generated from the brain nerves and an information signal to indicate the cerebrum activity. Using the analogy of a flowing river, the purpose is not to measure the height from the bottom to the surface, but to rather measure the ripples on the surface. There are basically four different types of waves in an EEG signal. These are namely the delta, theta, alpha and beta waves. The delta wave band, with frequency less 4Hz, and the theta wave band, frequency between 4 and 8Hz, are the slow waves, while the alpha wave band (8-13Hz) and the beta wave band (>13Hz) are the fast waves.

Normal EEG Waveforms*:* When an EEG waveform is recorded for a patient who is awake or at rest or with eyes closed, a wave about 1Hz in frequency and 50 microvolts in amplitude is continuously generated from the occipital region in almost symmetrical fashion in left and right sides of the brain while it becomes larger and smaller (waxing and waning) just like the tide rises and falls [5]. This wave is called the alpha wave and is considered as a standard wave of a normal patient. Figure 2 shows part of an EEG graph of a normal patient captured over a few seconds.

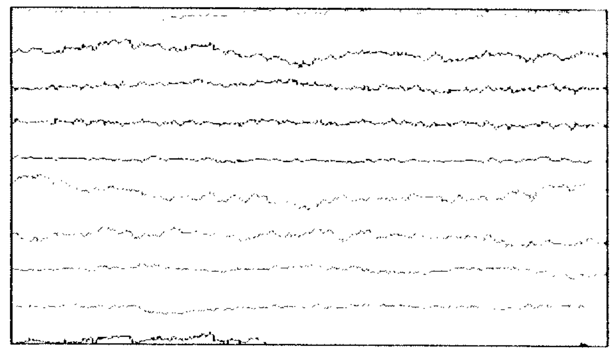

Figure 2: A normal EEG graph (300 x 300 pixel)

Abnormal EEG Waveforms*:* Pattern recognition in an abnormal patient usually includes the appearance of a spike, sharp wave and slow wave complex. Between these abnormal waves an irregular slow wave appears and the background waveform is disturbed. These patterns occurring in the different wave bands aid a neurologist in identifying a normal and abnormal patient.

EEG inspection is indispensable to the diagnosis of tumours and epilepsy. The waveforms of epilepsy include idiopathic abnormal waves such as a spike, sharp wave and slow wave complex. Between these abnormal waves, and irregular slow wave appears and the background waveform is disturbed as depicted in figure 3. An abnormal wave sometimes appears isolated in the limited part or continues all over the waveform. The generating condition and form are different case by case. A general spike slow wave complex of 3Hz appears in the case of absence. Autonomic nerve fit is characterised by a positive spike of 14Hz or 6Hz. Nod spasm is characterised by seriously abnormal rhythm and called a wasting syndrome as seen in babies. Serious fit is normally accompanied by a spasm, and consciousness is lost. The EEG waveform in all these cases will have a continuos spike or sharp wave.

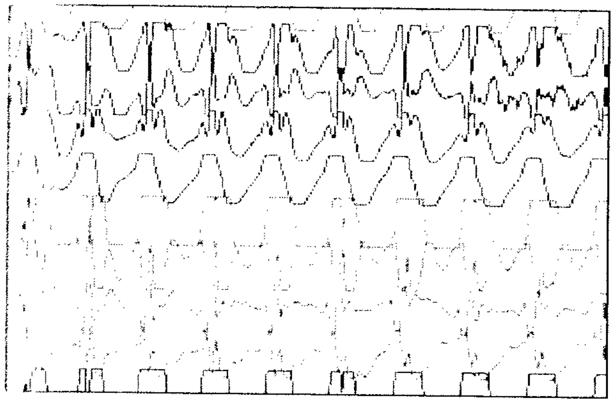

Figure 3: An abnormal EEG graph (300 x 300 pixel)

Figures 2 and 3 show that these EEG signals are non-linear and have a pattern that exist depending on the brain activity. The recognition of the brain activity will require clean signals and expertise to classify them. Sometimes it is difficult even for the experienced neurologist to categorically classify the brain activity based on these signals.

3. Artificial Neural Network Based EEG Classifier

3.1 EEG Sample Acquisition

The EEG samples used in this study are captured in the EEG Neurology department of the Wentworth hospital in Durban. In total thirty EEG signals were captures, of which fifteen are of normal patients and other fifteen are of brain tumour patients. EEG waveforms patterns differ with age of the patients.

Generally, waveforms of infants are slower than those of adults. This tendency decreases as the age rises, theta and alpha waves of 7 to 8Hz appear in the occipital region in children of 4 years. In 9-year-old children, an alpha wave of about 10Hz appears in occipital region. After 15 years old, the EEG waveforms become almost the same as those of adults. Judging from the EEG waveform, 15 to 60 years old are adults. Even during these ages, the slow waves decreases as the age rises and the fast wave increases. Over 60 years old, the slow wave increases again as the age rises. It was decided to target a specific age group for the selection of data samples. The age group selected was for individuals from the age of 30 to 50.

The equipment that was used to capture the EEG signals at Wentworth hospital is the Nihon Kohden, Neuropak EEG-100. The EEG signals captured were stored on the Neurofax EEG-100, version 03-01 database. Each patient was subject to a minimum of 20 minutes of evaluation, where the probes are stuck onto the patient's scalp to capture the EEG recording. Each signal capture consists of 17 channels. Sixteen channels are for the probes around different areas (montage pattern – left and right occipital region) of the scalp, whilst the seventeenth channel is used in capturing the ECG signal of the patients pulse. The sampling rate for the capture of the signals was set at 500Hz by the manufacturers of the equipment. The database was then analysed to choose the correct signals that were to be trained and tested by the neural network. The manufacturing equipment was also configured to remove the artifacts and noise as much as possible. The sample signals used for training the ANN were confirmed as EEG signals of brain tumour patients by the neurologist and further tests to ascertain the nature of the tumours, and the validity of the EEG recordings was also carried by the neurologist.

3.2 Artificial Neural Network and its Architecture

Artificial neural networks (ANNs) have become very popular for data analysis over the past 2 decades. ANNs have evoked into a powerful tool for solving intelligent tasks in automation and speaker identification [6]. ANNs are intelligent systems that are based on simplified computing models of the biological structure of the human brain. Whereas traditional computer logic – based systems require comprehensive programming in order to perform a given task. Artificial neural networks are inherently able to infer what needs to be done by simply observing data that is representative of the underlying process to be implemented [7, 8]. The self-learning ability of ANNs is particularly useful where the comprehensive models that are required for conventional computing methods, are either too large or complex to represent accurately, or simply does not exist at all. The highly connected, distributed nature of the ANNs also lends them a high degree of noise immunity, fault tolerance and generalisation capability.

For the application described in this paper, EEG analysis, the feedforward neural network is used to demonstrate the capability of ANNs. In this investigation a multi-layer feedforward (MLFF) neural network is implemented. The backpropagation-training algorithm is used to train the ANN. Generalisation is perhaps the most useful feature of a backpropagation network. Since the network uses supervised training, a set of input patterns can be organised into groups and fed into the network. The network will 'observe' the pattern in each group, and will learn to identify the characteristics that separate the groups. Input vectors and their corresponding output vectors are used to train a network to approximate a function, associate input vectors with a specific output vector, or classify input vectors in a way pre-defined by the user.

Figure 4 shows a block diagram of the ANN based EEG classifier system. Figures 2 and 3 were typical EEG graphs that were presented as inputs, after they have been pre-processed into a format presentable (discussed in the next section) to the ANN.

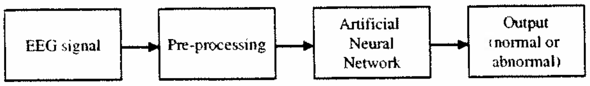

Figure 4: Block Diagram of ANN based EEG classifier

3.3 Pre-processing of ANN Inputs

Image pre-processing involved the scanning of the EEG waveforms into bitmap files, which where then converted to black and white. The images where then resized to a 300 by 300 pixel image, with greyscale and 8 bits/channel. The converting of the images to bitmap allowed for it to be read straight into MATLAB, using the 'imread ' command found in the MATLAB toolbox. A trained data set was created which was then used to train the network. In this application twenty samples were used to train the network. There were ten samples that were of a normal EEG signal, whilst the other ten EEG signals were of patients who were diagnosed with brain tumours. The images where converted into a 10x10 vector matrix, then reshaped to a (100x1) vector matrix and each pixel served as an input to the network. The network was then trained randomly with all the inputs and their corresponding targets. The neural network has two possible outputs, normal and abnormal.

3.4 Training of the EEG ANN Classifier

Initially the architecture of the multi-layer feedforward (MLFF) neural network was set at 100:30:1 (100 neurons in the input layer, 30 neurons in the hidden layer, and 1output neuron) as depicted in figure 5. The EEG sample inputs were being trained in an orderly fashion, all abnormal followed by the normal inputs. However, during the testing of the training samples, the neural network was not able to correctly recognise and classify all the inputs. It was then discovered that the neural network was not training properly as all the abnormal samples were trained first followed by the normal samples. This meant that at the end of the training the neural network had 'forgotten' sufficient information, patterns of the abnormal inputs. The network was then trained with random abnormal and normal inputs, and it then correctly classified all of the twenty training samples as shown in section 4.

4. Results

The ANN had to be trained further on the training set and tested on a test set of samples. At the start of the training, the weights of the ANN were assigned random values; hence the training time differs every time although the same inputs are applied. When the weights are stored in the system, the new training may not take as long because the system will make use of the stored weights. The network was trained numerous times and it was clearly noted that the training time was reducing and recognition was improving. The training time reduced because the weights were being set closer and closer to the desired values. Each time a copy of the weights were made and the network then trained from those values instead of random values. This reduced the training time and improved performance. The number of neurons, error goal and number of epochs where also varied to improve performance. Once the network was effectively recognising, the error goal, number of epochs and the number of neurons were reduced to make the network more stringent. Reducing the error goal decreases the degree of error. This means that the room for error is being reduced to a bare minimum. Reducing the number of neurons makes the ANN much smaller hence reducing processing time and making the network more efficient

Twenty different EEG samples, normal and abnormal, were used for the training of the ANN. In addition ten different EEG samples, normal and abnormal, were used to test the trained ANN. Figures 6 and 7 show a normal and an abnormal EEG signal respectively used to test the ANN EEG classifier.

Table. 1 shows the training and testing results of the ANN classifier with a 10 x 10 matrix input. . The ANN gives a 100% classification success rate with both normal (N1-N15) and abnormal (A1-A15) EEG. This is as a result of good training that ensures global convergence of the ANN weights with random normal and abnormal EEG signal training samples.

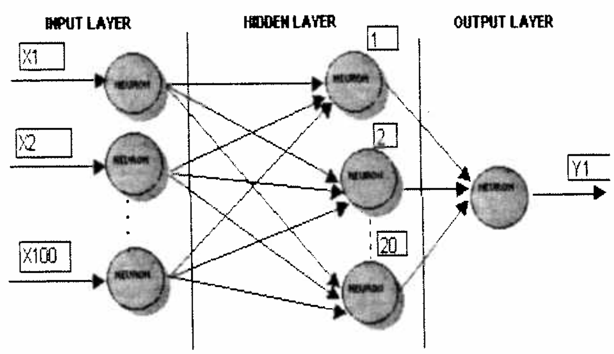

Figure 5: The MLFF architecture used in this ANN EEG classifier.

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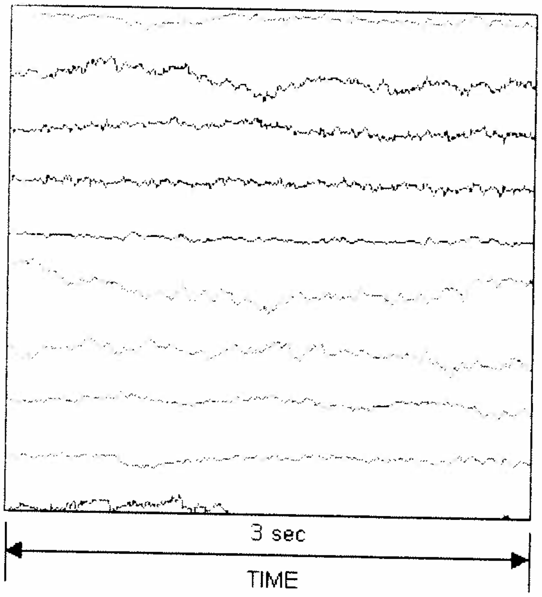

Figure 6: A normal EEG test signal.

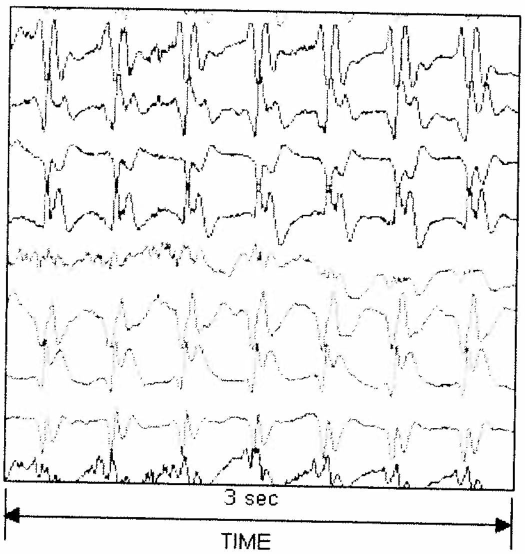

Figure 7: An abnormal EEG test signal.

Table 1: Training and testing results for the ann classifier with a 10 x 10-matrix input

TRAINING SAMPLES			
INPUTS	DESIRED O/P	ACTUAL O/P	Correct Classification
A1 - A10	Abnormal	Abnormal	100%
N1 - N10	Normal	Normal	100%
EXTERNAL TESTING SAMPLES			
INPUTS	DESIRED O/P	ACTUAL O/P	Correct Classification
AT1 - AT5	Abnormal	Abnormal	100%
NT1 - NT5	Normal	Normal	100%

A further investigation was carried out where the inputs (size of the matrices) fed into the system was changed under the same network operating parameters which meant that the previous network that was trained with the 100 x 1-matrix inputs would remain intact with all its parameters (error goal, momentum constant, etc). The comparison would be between the results achieved with different matrix sizes (10 x 10, 100 x 100, 300 x 300) of the same inputs. The results gathered indicated that the larger the input matrix the longer the time the neural network took to train. The success rate of the classification also decreases, as the input matrix size increased. The training times, and number of epochs taken to train the networks are illustrated in table 2 and table 3. It is evident from the results that as the number of hidden neurons increased, so did the training time also increase, while the training time decreased as the error goal was set to a lower constant. Figure 8 is a bar graph that illustrates the accuracy of the successful classification achieved for the different image sizes.

Table 2: Results of the different image size training with an error goal of 0.01

ERROR GOAL = 0,01			
	image size	**20 hidden neurons**	**30 hidden neurons**
	10 x 10		
time to train		16.81sec	19.39sec
no. of epochs		1403	1285
accuracy		100%	100%
	100 x 100		
time to train		9min 16sec	13min 58sec
no. of epochs		852	870
accuracy		90%	90%
	300 x 300		
time to train		30hours 27min	37hours 19min
no. of epochs		810	780
accuracy		90%	90%

Table 3: Results of the different image size training with an error goal of 0.0001

ERROR GOAL = 0,0001			
	image size	**20 hidden neurons**	**30 hidden neurons**
	10 x 10		
time to train		32.79sec	35.21sec
no. of epochs		2720	2522
accuracy		100%	100%
	100 x 100		
time to train		14min 36sec	25min 20sec
no. of epochs		1331	1312
accuracy		93.33%	90%
	300 x 300		
time to train		34hours 46min	43hours 19min
no. of epochs		1302	1280
accuracy		90%	86.66%

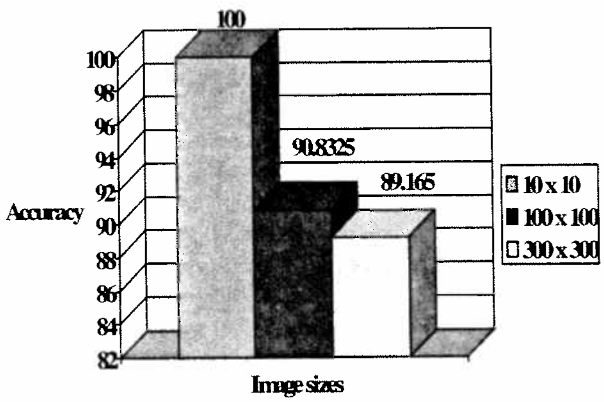

Figure 8: Bar graph of the accuracy achieved for the different image sizes

5. Conclusion

The results in this paper show that an artificial neural network is able to distinguish between an abnormal and normal EEG signal, and classify them correctly as brain tumour and healthy patient respectively. This is possible with ANNs since they are able learn the patterns in a normal and abnormal EEG signal. This technique can be extended to train artificial neural networks with different types of brain disorder. The advantage of using ANNs is that they will be consistent on their outputs provided sufficient training is given offline. Furthermore, they have the capability of making smart decisions on inputs that may be slightly different from ones they were trained on.

The use of an ANN based EEG classifier will benefit the hospitals especially where experts in EEG analysis are not available and also assist experts in screening EEG readings faster.

6. Acknowledgement

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