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PHYSIOLOGICAL ANALYSIS OF HYPERTENSION PATIENTS BY MONITORING THE BRAIN WAVES

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ABSTRACT

The inability and the negligence in the detection of diseases is a major reason in the delay of treatment which may prove fatal. It is not possible for regular checkups in this time deprived world. Moreover, regular checkups are not feasible to everyone. The brain is the most interesting part of the human body. It controls the vital functions of the body and therefore any abnormality in the brain will reflect in the entire body and vice versa. The control of the brain is by the transmission of electric signals from and to the various parts of the body. The study and observation of these electrical signals will help us to find a lot of abnormalities which occur in the brain. Hence, this proposed work aims at overcoming the deficiency in time and money needed for the regular checkups. This is achieved by monitoring the brainwaves of the patient. The brainwave pattern of the patient is compared with the normal brainwave pattern. If an anomaly is observed in the patient's brainwave pattern further comparisons with disease brainwave patterns are made. The disease pattern which matches with the patient's pattern is identified as the disease. The patient is recommended for further tests on the disease. In this work, only hypertension patients are considered for the study of physiological analysis using Weka tool.

Index Terms— Physiological Analysis, Brain Waves, Electroencephalograph (EEG), Confusion Matrix, Weka Tool.

I. INTRODUCTION

The International Federation of Societies for Electroencephalography and Clinical Neurophysiology name the five brainwave frequency bands as alpha, beta, gamma, theta and delta. Our brain waves change spontaneously based on our emotions. The brain wave frequencies are measured in Hertz like other signal frequencies.

Delta waves in the range of 0.5 to 3 Hertz indicate inactivity or relaxation and are observed during our deep dreamless sleep [1]. The delta waves are slow and reflect the relaxed state of the brain. Theta waves range from 3 to 8 Hertz and occur during sleep or when the person is in deep meditation.

Alpha waves have a range between 8 and 12Hertz. They are observed during an idle state of the brain like daydreaming and conscious meditation. Beta waves are fast waves measured in the range of 12 to 30Hertz and contribute to the frequencies of consciousness like reading about this work and occur when attention is focused on a task [2].

Beta is a rapid wave activity observed while problem solving and decision making. Depression and anxiety are also linked to beta waves.

Gamma waves range between 25 to 100Hertz and is the fastest of the brain wave bandwidths. Gamma waves are observed during conscious perception of environment and are greatly observed in emergency situations.

The electroencephalogram (EEG) is a graph which records the electrical signals created by the interaction of neurons in the brain. The process to obtain an EEG is tedious and uncomfortable. A fast and easy substitute for the detection of brain signals is the brain wave sensor. The brainwaves obtained from the brain using the brainwave sensors are observed, compared and analyzed to detect the abnormalities in the body. The brain wave pattern is then studied to detect the affected area in the early stages and recommended for treatment. This device can also be used as a communication or alert mechanism for patients completely paralyzed or patients to be monitored continuously [3, 5].

In this work, the patient's brainwaves under different emotions are extracted. The extracted measurements are then analyzed, compiled and stored as a comma separated value (csv) file. The csv file is then compared and analyzed with the normal and disease pattern csv files using the Weka tool. The inference from the correlation percentage and correlation matrix will help to recommend further tests on a particular disease. Table 1 shows the brain states associated with different frequency bands.

Table 1 Brain States Associated with Different Frequency Bands

Wave type	Frequency range (in Hz)	Emotions	Hormones
Delta	0.5-3.0	Dreamless sleep	Melatonin
Alpha	8.0-12.0	Daydreams, Relaxation	Serotonin
Beta	12.0-30.0	Alertness, Concentration	Dopamine
Gamma	25.0-100.0	Conscious perception	Adrenaline
Theta	3.0-8.0	Deep relaxation, REM sleep	Anti-cortisol

II. RELATED WORKS

This section briefly describes the related works carried out for the proposed study. Brainwaves were originally used for diagnosing epilepsy and other brain related diseases. Brainwaves are measured from a T-20 standard electrode position. These measurements are used for the diagnosis of diseases affecting the brain. Our work involves recording the brain waves of the patient and comparing them with disease signal for identifying hypertension in patients [6].

A correlation between increased alpha waves through meditation and the ability to reduce depressive symptoms and increase creative thinking was made by the neuroscientists recently. The state of consciousness is an effect of the electrical, chemical, and architectural changes which take place in the brain. The behavioral and thought processes can alter the neurochemical and electrical oscillations in the brain [7, 8].

The brain consists of billions of neurons that use electricity to communicate with one another. Brain waves can be detected using medical equipment, such as brainwave sensors, which measures the oscillation of electricity levels in different areas of the brain [9, 10]. In [11], Karim et al proposed a neural network classification for web surfing problem using EEG waves of the paralyzed patients.

Neuroscientists at Brown University published their study in the Journal of Neuroscience, Attention Drives Synchronization of Alpha and Beta Rhythms between Right Inferior Frontal and Primary Sensory Neo-cortex [12].

III. PROPOSED WORK

The sensors pick up the brainwaves at the forehead and the ear. The brainwaves from the two points are subtracted and amplified to enhance the faint signals. The signals are passed through analog and digital low and high pass filters in the 1-50Hz range are retained. The signal is rechecked for noise and the useful part of the signal is transmitted via Bluetooth to the EEG reader app.

The raw EEG signal from the brainwave sensor given to the EEG reader app. The signal is sampled at intervals provided by the user in seconds. The signal values are grouped into attention and meditation values and stored into a csv file. The csv files of the brainwave signals of the patient is taken at different intervals and combined into a single csv file. This csv file is given to a data analytics tool called 'weka' for the correlation with the normal dataset. The correlation is done and the correla-tion percentage is calculated. If the correlation percen-tage is low, then further tests with disease patterns are made.

The EEG signal from the neurosky device is given to the EEG reader app which converts it into a csv file. The csv files of the brainwave signals of the patient is taken at different intervals and combined into a single csv file. This csv file is given to a data analytics tool called 'weka' for the correlation with the normal dataset. The correlation is done and the correlation percentage is calculated. If the correlation percentage is low, then further tests with disease patterns are made. The system model of the proposed work is illustrated in Fig. 1.

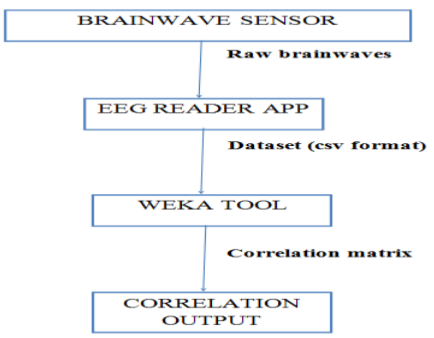

Fig. 1. System Model

IV. EXPERIMENTAL RESULTS

The brainwave sensor is placed correctly on the patient's head and the brainwaves are transmitted to the EEG reader app using Bluetooth as shown in Fig. 2.

The EEG Reader app retrieves the brainwave signals from the headset (Neurosky starter kit) via Bluetooth. The attention and meditation readings are depicted graphically as shown in Fig. 2. The average will be calculated for the specified interval for both attention and meditation to achieve greater accuracy. The readings will be exported to csv (Comma Separated Values) file format for further processing using Weka tool.

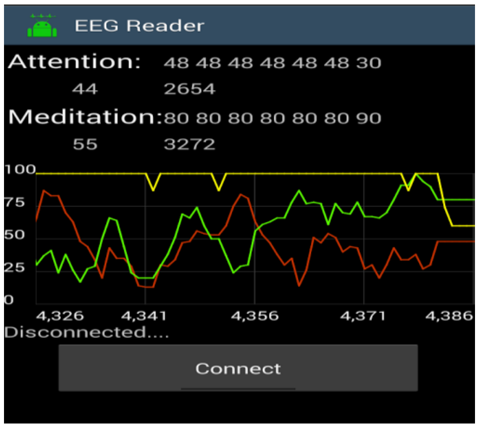

Fig. 2. EEG Reader App

The brainwaves can be visualized as a graph of attention level and meditation level in the app. When the brainwaves have been observed for a certain time records are added to the csv file. The csv file is opened in the weka tool explorer. After opening the csv file, in the select attributes tab, the principle components chosen as attribute selector and ranker is chosen as search method as shown in Fig. 3.

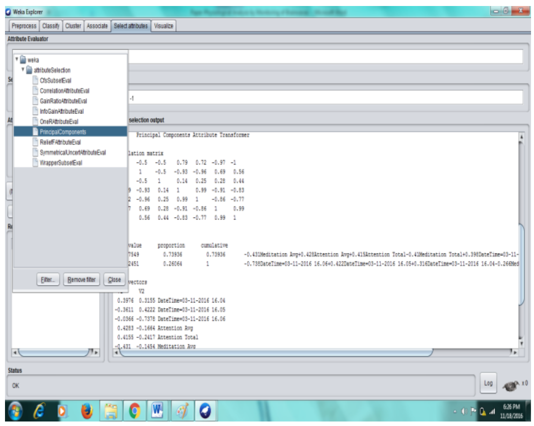

Fig. 3. Weka Tool Screenshot - Select Attributes Tab

The correlation percentage is calculated and the result is displayed.

V. INTERPRETATION

The confusion matrix is used for assessing the performance of the classification model for the given data sets. Let us explain with an example for binary classification (it can be extended to any number of different class labels) as described in Table 2.

Table 2 Confusion Matrix for a Binary Classifier

N = 150	Label predicted: no	Label predicted: yes
True label: no	70	50
True label: yes	10	20

Observations from the matrix:

The two possible predicted class labels: "yes" and "no". If the label was "yes" then the disease is present for the patient else not.

Out of 150 predictions (e.g., 150 patients were being tested for the presence of that disease). The model predicted "yes" 60 times, and "no" 90 times.

Ninety-five patients in the sample have the disease, and 55 patients do not.

Let's now define the most basic terms, which are whole numbers (not rates):

- true positives (TP): These are cases in which we predicted yes (they have the disease), and they do have the disease.
- true negatives (TN): We predicted no, and they don't have the disease.
- false positives (FP): We predicted yes, but they don't have the disease. (also, known as a "Type I error.")
- false negatives (FN): We predicted no, but they do have the disease. (also, known as a "Type II error.")

We have added these four terms to the confusion matrix, and added the row and column totals as shown in Table 3.

Table 3 Confusion Matrix for a Binary Classifier with TP, TN, FP and FN

n=165	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

This is a list of rates that are often computed from a confusion matrix for a binary classifier:

Accuracy: Overall, how often is the classifier correct?

- (TP+TN)/total = (100+50)/165 = 0.91

Misclassification Rate: Overall, how often is it wrong?

- (FP+FN)/total = (10+5)/165 = 0.09
- equivalent to 1 minus Accuracy
- also known as "Error Rate"

True Positive Rate: When it's actually-yes, how often does it predict yes?

- TP/actual yes = 100/105 = 0.95
- also known as "Sensitivity" or "Recall"

False Positive Rate: When it's actually-no, how often does it predict yes?

- FP/actual no = 10/60 = 0.17

Specificity: When it's actually-no, how often does it predict no?

- TN/actual no = 50/60 = 0.83
- equivalent to 1 minus False Positive Rate

Precision: When it predicts yes, how often is it correct?

- TP/predicted yes = 100/110 = 0.91

Prevalence: How often does the yes condition actually occur in our sample?

- actual yes/total = 105/165 = 0.64

Positive Predictive Value: This is very like precision, except that it takes prevalence into account. In the case where the classes are perfectly balanced (mean-ing the prevalence is 50%), the positive predictive value (PPV) is equivalent to precision.

Null Error Rate: This is how often you would be wrong if you always predicted the majority class. (In our example, the null error rate would be 60/165=0.36 because if you always predicted yes, you would only be wrong for the 60 "no" cases.)

Cohen's Kappa: This is essentially a measure of how well the classifier performed as compared to how well it would have performed simply by chance. In other words, a model will have a high Kappa score if there is a big difference between the accuracy and the null error rate.

F Score: This is a weighted average of the true positive rate (recall) and precision.

ROC Curve: This is a commonly used graph that summarizes the performance of a classifier over all possible thresholds. It is generated by plotting the True Positive Rate (y-axis) against the False Positive Rate (x-axis) as you vary the threshold for assigning observations to a given class. Following Table 4 describes the test records for this analysis.

Table 4 Test Records

Date and Time	'Attention Avg'	Attention Total'	'Meditati-on Avg'	'Meditati-on Total'	Class
03-11-2016 16.04'	64	3895	42	2564	yes
'03-11-2016 16.05'	48	2922	54	3256	yes
'03-11-2016 16.06'	58	3623	51	3199	no
05-11-2016 16.04'	74	4095	52	2554	yes
05-11-2016 16.05'	45	2632	39	2256	yes
05-11-2016 16.06'	57	3623	54	3199	no
07-11-2016 16.04'	64	3895	53	2554	yes
07-11-2016 16.05'	74	4095	44	2284	yes
08-11-2016 16.06'	55	3623	54	3199	no
08-11-2016 16.04'	45	3456	39	2256	no
08-11-2016 16.05'	48	2922	64	3256	yes
08-11-2016 16.06'	68	3623	54	3199	no
09-11-2016 16.04'	74	4095	54	2554	yes
09-11-2016 16.05'	72	2922	67	3256	yes
10-11-2016 16.06'	48	2632	39	3456	yes

10-11-2016 16.04'	88	3675	54	2554	no
10-11-2016 16.05'	67	2922	67	3256	yes
14-11-2016 16.06'	88	4095	45	3864	yes
14-11-2016 16.04'	48	3895	54	2554	no
14-11-2016 16.05'	65	2632	39	2966	yes
15-11-2016 16.06'	54	3623	54	3199	no
16-11-2016 16.04'	43	4095	54	2554	yes
16-11-2016 16.05'	48	2632	39	3000	yes
17-11-2016 16.06'	48	4323	54	3199	no

Table 4 contains a set of training dataset in which each record is associated with a class label. The records associated with the class label are used for creating a learning model for predicting the class label for the new/unseen records. Based on the test records, the Weka tool plots the outputs of the correlation between the records in the dataset as X-Y plot as shown in Fig. 4.

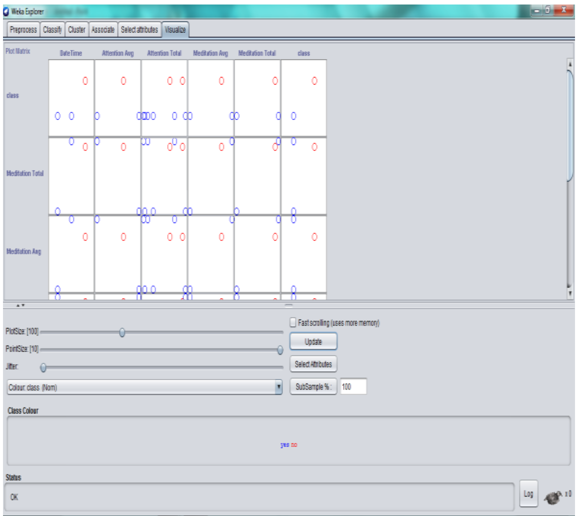

Fig. 4. Weka Tool Screenshot – Visualization Graph

Weka tool plots the output of the correlation between the records in the dataset and clusters them into two classes namely "yes" and "no". In Fig. 4, the X and Y axes represent one of the parameters such as attention, mediation etc. The projection mark (o) in the graph indicates the record of the patient and whereas the colour (Blue = "yes", Red="No") indicates the class label. We can adjust the dataset aliasing by using the jitter as shown in Fig. 4, which introduces random noise in the data. The cluster closer to the attention level of the diseased patients reveals the patients having the disease.

VI. Conclusion

Our work currently focuses on the hypertension in patients and the detection of the condition using brainwaves. We are looking forward to expand the range of medical conditions which have a major impact on brainwaves like brain tumors, epilepsy, Parkinson's disease, Amyotrophic lateral sclerosis (ALS), epilepsy, stroke, and cardiology disorders like cardiac arrest, atherosclerosis, coronary artery disease and peripheral artery disease. Since the brainwaves pattern obtained from the sensors are not dependable completely, further enhancements in sensors may improve the quality of detection.

This proposed work also has a scope for an alert system for patients who need continuous monitoring like patients who suffer from paraplegia, quadriplegia, muscular dystrophy, cerebral palsy etc. The scope and value of this research increases with integration to wearable devices providing continuous assessment of the body condition.

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