MODELING HUMAN DOUBT TO CREATE DECISION ANALYZER FOR A ROBOT

[1]Oyinloye Oghenerukevwe E., [1] Edward. A. Ajayi & [2]Thompson Aderonke F.
[1] Department of Computer Science, Ekiti State University, Ekiti-State, Nigeria
[2]Department of Cybersecurity, Federal University of Technology Akure
oghenerukevwe.oyinloye@eksu.edu.ng, Ojayedwards1@yahoo.com, tonyfav24@gmail.com

ABSTRACT

The concept of human doubt as a suspense between two or more contradictory propositions covers a range of phenomena: on a level of the mind, it involves reasoning, examination of facts and evidence and on an emotional level, believing and disbelieving. False tagging theory (a neuroatomical model of belief and doubt processes) asserts that the prefrontal cortex is critical for false tags during the assessments of beliefs. The juxtaposition of a false tag on a "Perceptual cognitive representation (PCR)" which refers to any belief substrate that creates a dispositional doubt for the particular belief receiving the tag and FTT affirms that the prefrontal cortex performs the singular function of false tagging for disparate modalities which compete for these resource in a flexible manner. In our bid to explore the concept of doubt in the human brain, brainwave signals (a bioelectric phenomenon reflecting activities in the human brain) is measured using Electroencephalography. The EEG data used in this project was simulated using SEREEGA (A Matlab toolbox for simulating Event-Related EEG) to reflect the doubt activities (a function of prefrontal cortex) in the human brain. During the modelling process of the EEG data, MATLAB programming language was employed and EEGLAB and BCILAB Matlab toolboxes are used. The EEG data is subject to features extraction and classification. Linear Discriminant Analysis (LDA) is the machine learning technique used for classification and Area under ROC is the performance metric used and we achieved a classification accuracy of 95% which has been able to meet the needs of real applications.

Keywords: Doubt, False Tags, False Tagging Theory, EEG, Feature Extraction, Classification.

INTRODUCTION

Human doubt is a mental state in which the mind remains suspended between two or more contradictory propositions unable to assent to any of them. Doubt for a specific belief can have variety of effects which are often realized as a reduction of behavior toward the belief *(Asp, 2012).* Human doubt being a brain activity can be recorded for used as a biometric factor in building mind-machine interface security systems through Electroencephalography (EEG) which has proven to be the most preponderant approach to human mind security.

Human behavior modeling can help understand, compute, simulate, and predict human behaviors *(Pentland & Liu, 1999),* and these modelling can provide insights into the development of human centered security control techniques by integrating the behavioural activities prediction into the security or access control strategy. EEG data recorded from subjects during any activity can be modelled using various machine learning techniques and this helps get a better understanding of a particular human activity which can then be embedded or adopted in building security or access control systems.

According to *Gui et al. (2015),* it is almost impossible for one individual to simulate the readings of another, as individual brain activities are unique, being patterns of neural pathways

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of any one human being; they are connected into a subject's unique memory and knowledge. In addition, because the brain signals are associated with an individual's emotions, it is very difficult to obtain them using threat and force. Therefore it is employed in nowadays biometrics which are used in access control systems because it is safely protected inside the skull and our brain activities are changeable *(Karthikeyan and Sabarigiri, 2011).* Hence, modelling human doubt not only help a system authenticate a user but it gives the system the ability to check the level of uncertainty experienced by the user during a decision making process and deny access to the user if he/she is experiencing doubt.

Related Works

In order to gain in-depth knowledge of EEG signals and its processing techniques, previous research work is reviewed in this section.

Mochachandra et al, (2013) developed a system that enable the technique of using brainwaves as a biometric factor to authenticate users in real time. It was built to maintain and manage access to a user's platform and to protect user's identity and computer resources. Datasets from normal subjects are recorded for two active cognitive tasks (Meditation and Math Activity) during each recording session. For the meditation activity, the subject is asked to meditate for a fixed period of time while his brain waves are recorded while during the Mathematics activity, the subject is given non-trivial multiplication problems, such as 79 times 56 and is asked to solve them without vocalizing or making any other physical movements. The problems were designed so that they could not be solved in the time allowed. These EEG signals are then segmented and channel spectral power for 3 spectral bands (Alpha, Beta and Gamma) are computed and used in the classification task. A two stage authentication is done to authenticate the user and a proximity value of 0.78 is considered a good match.

Hadi and George, (2017) developed an Electroencephalography based user identification method using two separate set of features which are energy distribution based on Discrete cosine transform (DCT) AC components and the statistical moments for the three types of wavelet transforms. Two EEG Datasets used in this work are EEG CSU Dataset (where subjects performed mental tasks such as Baseline tasks, letter composing tasks, mathematics tasks, rotation tasks and counting tasks) and Motor movement/Imagery dataset (where subjects performed movement and imagined movement tasks) were used and during feature extraction, time-to-frequency domain mapping step is applied using proposed transform methods which include DCT, Discrete wavelet transform (DWT), Dabuchies wavelet transforms and bi-orthogonal wavelet transforms. After DCT step, then the obtained (AC) coefficients are divided into a number of blocks (or bands) and the energy of each block is calculated by taking the average of each block. Each block average represents one feature. The energy based features are used to generate feature vector. Then Linear Discriminant Analysis (LDA) is applied for feature analysis and combination to select the best set of features that gives the best recognition rate.

Gutierrez, (2017) proposed an electroencephalograph biometric for Android OS using EEG workbench. This system is built to provide stronger security for mainstream computing platforms and also, to improve upon traditional keyboard input schemes by directly replacing keyboard input or by utilization as a second factor. Acquired EEG signal is taken by the pre-processing module from the signal acquisition module where all unwanted artifacts are removed. The EEG signal then undergoes spectral analysis to interpret the signal in the time and frequency domain. Then, the feature extraction module takes cleaned EEG signal and best features (specifically, features for which frequency bands) are or use in authentication are extracted using wavelet transform and the Hjort parameters are used to assist in indicating the statistical property of the signal. Support vector machine (SVM) and Multi-Layer Perceptron (MLP) are the classifiers used.

Palaniappan, (2007) modelled a novel biometric identifier for small population. EEG signal was extracted during mental activities which are; Math activity (Solving nontrivial multiplication problems without vocalizing or making any physical movements and no subject completed the activity before the end of 10 seconds recording session), Geometric figure relation activity, Mental letter composing activity and visual counting activity. Elliptic finite impulse response was used to high-pass filter the EEG signal to reduce noise and extract EEG signals of three spectral bands Alpha (8-13Hz), beta (14-20Hz) and gamma (21-50Hz). Forward and reverse filtering are done to ensure that there will be no phase distinction. The EEG signals are subjected to feature extraction using Auto-regressive (AR) modelling where six AR coefficients (features) are obtained for each EEG channel for each mental activity and computation of channel spectra power and inter hemispheric channel spectral power differences gives nine spectral power differences (features) for all the channels for each frequency band. Computation of Inter-hemispheric channel linear complexity is also done. The standard PCA algorithm was used to reduce the feature size. Linear Discriminant Classifier is used to classify the feature vectors.

Zhendong and Jianfeng, (2011) researched on EEG identification computing based on photo images to achieve their aim of using induced EEG signals as identification code/ passwords for subjects. Different subjects were shown recent photos of recent upper body randomly displayed at the rate of 5/1400Ms and subjects were asked to remember the number of photos in each experiment during which EEG signal is recorded. These recorded EEG signal are then sent to the pre-processing stage where larger drift of EEG such as movement and blinking that can affect the calculations are removed. Then, auto-regressive (AR) model is used to convert the EEG signal from time domain to frequency domain and to extract the features from frequency domain signal. Fisher distance is used to generate the mean and standard deviation of these features. Back propagation neural network is trained to establish the classification of individuals.

Hadi and Georg, (2015) developed an EEG based user identification and verification using the energy of sliced Discrete Fourier Transform (DFT) spectra. EEG CSU dataset of subject performing mental tasks were taken, then DFT was used to decompose the input signal into two set of signal which contain the sine or cosine series of the input signal. Power spectra consists of the sine and cosine components and it also contains the AC (Alternating components used to extract the main features that are used to recognize each class. A quick DFT algorithm is used to speed the mapping task for time to frequency domain. In the Fourier transform, an EEG signal is applied using the following general mapping equation then the extracted features are fed as input to the feature analysis stage to select the best discriminative features with lowest intra-distance and highest inter distance which in turn leads to reduce the feature vector size. LDA is used to select features which minimize intra-class distance and maximize the inter-classes distances. In the matching stage, the degree of similarity between extracted pattern and stored templates are calculated using Euclidean distance measures which are normalized mean absolute difference and the normalized mean square difference. The system achieved a perfect recognition (100%) for identification.

Armstrong et al, (2000) presents a method to determine how uniqueness, collectability and permanence are accessed for Event related potential (ERP) biometrics. It was designed as a biometric challenge protocol that taps access to the semantic memory of users. Event related potential (ERP) was acquired from subjects as they viewed seventy five acronyms intermixed with fillers from other lexical types. Acronyms were repeated once at a lag of 0, 2 or 3 intervening items. First responses to acronyms were used for training, and second responses were used for testing. Four different classifiers are used to quantify the distinctiveness of the ERP's acquired. Cross correlation, Divergent Auto-encoder (DIVA), Naïve discriminant learning and Support vector machine (SVM) are for training and testing the data for identification accuracy and confidence intervals were used.

Palaniappan, (2013) researched on method of identifying individuals using VEP signals and Neural Network. This system is developed to serve as a biometric to identify individual. VEP (Visually evoked potential) signal recorded while subjects are perceiving a single picture were filtered using a Zero phase Butterworth bandpass digital filter and gamma band spectral power and spectral power ratio is computed as the features to be used for identification in the system. A multi-layer perceptron neural network with a single hidden layer trained by Back propagation algorithm is used to classify the VEP spectral power ratios in the particular individual class. The result obtained in the experimental study give recognition accuracy close to 100%.

Methodology

In this section of the study, methodologies of this research will be discussed. As in most EEG authentication systems, there are two processes involved in brain activity-based biometric authentication systems: The enrolment process and the authentication process. In the enrollment process doubt activities are recorded in order then to be further examined for unique features used for authentication, and in this study, those features are modelled and saved. The second part is an authentication process that compares the features of newly acquired doubt activities with the already recorded features of those activities present in the form of a model.

Prefrontal Cortex in the Human Brain

The brain is an active organ with high complexity that acquires and processes the signals from the human body and environment, generates the responses accordingly and remembers the information when needed. It is a phenomenon that the brain presents behavioural and physiological information at the same time. Accordingly, it has huge significance for biometric purposes. Different kinds of brain signals produced by brain activity are recorded through EEG which is not only the fastest, but its characteristic are also unique for each individual *(Klonovs et al., 2012).*

From previous researches about the functioning of the prefrontal cortex in the human brain, *Asp and Tranel., (2012)* were able to assert claims about its functioning through which they developed False tagging theory (a neuroatomical model of belief and doubt processes) which asserts that the prefrontal cortex is critical for false tags during the assessments of beliefs. The juxtaposition of a false tag on a "Perceptual cognitive representation (PCR)" which refers to any belief substrate that creates a dispositional doubt for the particular belief receiving the tag and FTT affirms that the prefrontal cortex performs the singular function of false tagging for disparate modalities which compete for these resource in a flexible manner.

Data Acquisition

In the study of electroencephalography, brainwaves are divided into five frequency bands which are delta (0.5-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz) and gamma (30-50Hz) with each of these frequency bands having their own function and characteristics. Beta waves are characteristic of a strongly engaged mind.

MIT neuroscientists in 2018 have found evidence that the brain's ability to control what it's thinking about relies on low-frequency brain waves known as beta rhythms. In a memory task requiring information to be held in working memory for short periods of time, the MIT team found that the brain uses beta waves to consciously switch between different pieces of information. The findings support the researchers' hypothesis that beta rhythms act as a gate that determines when information held in working memory is either read out or cleared out so we can think about something else. The beta rhythm acts like a brake, controlling when to express information held in working memory and allow it to influence behaviour (Lundqvist, 2018). Therefore human doubt is believed to exist within the range of 13-30Hz which correspond to beta waves frequency with a specific characteristics that it is a feature of the prefrontal cortex called "false tags". In the 10-20 electrode system, EEG channels F3, F4, F7, F8, AF3, AF4, FC5, FC6, F_Z, Fp1, and Fp2 in the prefrontal cortex are selected. The PFC contains Brodmann areas (dipole source locations) which includes BA8, BA9, BA10, BA11, BA12, BA13, BA14, BA24, BA25, BA32, BA45, BA46 and BA47. Eight of these Broadmann areas are selected as dipole source locations where the EEG signals are generated.
SEREEGA (An open-source Matlab based toolbox) is then used to generate simulated Event related electroencephalography (EEG) data. Starting with a forward model (New York Head pre-generated lead field), dipolar brain components are defined and each component has its specified position in the brain. Different activation signals (ERP, ERSP and Noise) are assigned to these components and EEG data is simulated by projecting all the activation signals from all components into the scalp and summing them together. In matrix notation, this can be written as

$$\mathrm{X} = \boldsymbol{A_s} + \boldsymbol{€}, \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.1)}$$

With x denoting the vector of the recorded or simulated scalp signal, $\boldsymbol{s}$ the source activation signal, A the projection matrix used to project signals from the source to the scalp electrodes, and $\boldsymbol{€}$ denoting a vector of noise.

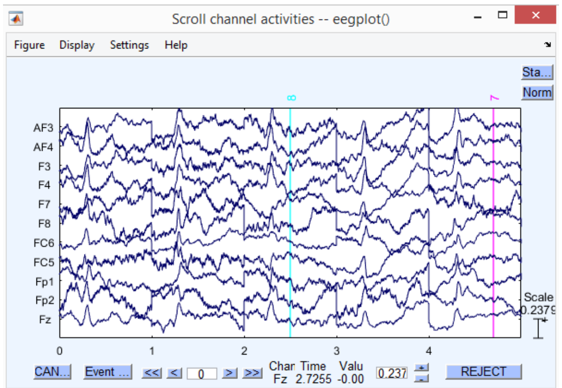

Fig 1. This figure above shows the simulated EEG data

Proposed Model Design

Consider an individual i has an EEG dataset of t unit of time. The m subdata sets of s unit of time $(s<t)$ are arbitrarily selected from the complete trace of an EEG. Then a vector of d-features is extracted from each subdata set. Let $P^{(i)}$ be the pattern matrix consisting of m vectors of individual i of size $m \times d$ that can be defined as;

$$P^{(i)} = \begin{pmatrix} f_{1,1} & f_{1,2} & \cdots & f_{1,d} \\ f_{2,1} & f_{2,2} & \cdots & f_{2,d} \\ \vdots & \vdots & & \vdots \\ f_{m,1} & f_{m,2} & \cdots & f_{m,d} \end{pmatrix}, \quad \ldots\ldots\ldots\text{(3.21)}$$

Where element $f_{j,k}$ represents the kth feature of the jth subdata set. The purpose of arbitrarily election of subdata set is to statistically analyze the variations present in different signal of an individual EEG. Consider the population size is n, so there are n different EEG datasets. Thus, n different pattern matrices $P^{(i)}$ are generated in the database in the database where $i = 1, 2, \ldots, n$.

Let an individual have a query sample Q that generates the feature vector $f' = \langle f'1, f'2, \ldots, f'd \rangle$. Statistically, the distance between the attributes of a query sample and feature vectors of a pattern matrix of an individual i is computed using Euclidean distance as follows:

then $d^{(i)}_j = (|f_{j,1} - f'_1|\ \ |f_{j,2} - f'_2| \cdots |f_{j,d} - f'_d|)$, ………(3.22)

Where $j = 1,2, \ldots m$. the sum of Euclidean distances of feature vectors gives the distance score measure for individual i, as

$$s_j^{(i)} = \sum_{k=1}^{d} \left| f_{j,k} - f'_k \right| \quad \text{……… (3.23)}$$

for all subdata sets $j = 1,2, \ldots m$. In order to acknowledge (incorporate) the variations present in the EEG data set of an individual i, the mean of the distance scores, denoted as $s^{(i)}$ can be computed and determined as follows

$$s^{(i)} = \frac{1}{m} \sum_{j=1}^{m} s_j^{(i)}. \quad \text{…………………… (3.24)}$$

A genuine match score is obtained when two feature vectors corresponding to the same individual are compared, and an impostor match score is obtained when feature vectors from two different individuals are compared. A smaller value of distance score indicates a good match while a higher value of distance score indicates a poor match.

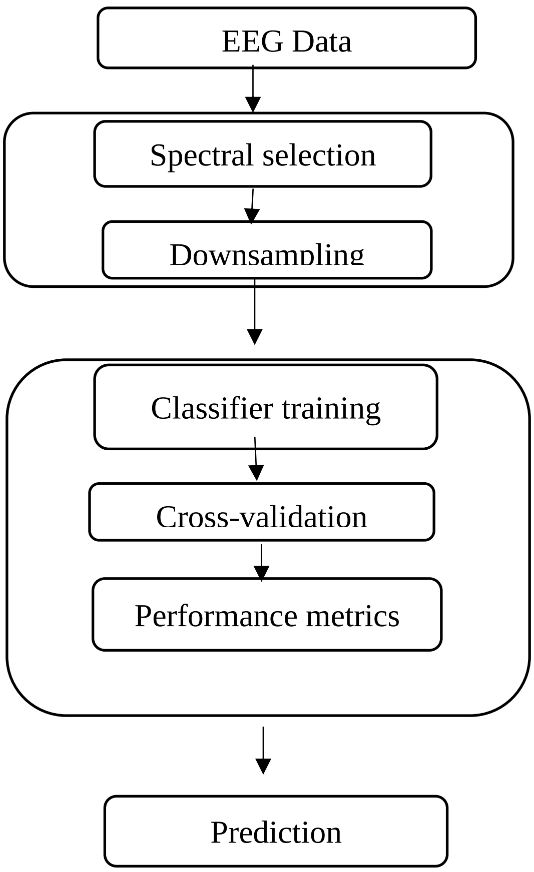

Fig 3.1. Architecture of the model

Phases of the Model

Feature Extraction

Among people, either during specific mental tasks or resting state, it is shown that specific features of the brain activity have different degrees of distinctiveness when dealing with EEG signals. Time and frequency are the two domains used mostly in which EEG features are extracted. In the feature extraction stage in this work, the spectral selection of the frequency band needed (12 – 30Hz) is done then, the data is downsampled from 1000Hz to 100Hz data rate to speed subsequent analysis. Epoch extraction is also done by extracting data epoch time-locked to the events of interest which begins 500ms before the time of event until 500ms after the event.

EEG Modelling

- *Classifier Training*

In the training phase, a 'one-versus-one' LDA model was trained for all the events in the EEG data, where the event labels (which contains numeric values) were '8', '7', '6' or '5'. The classification task was to best apply this event label appropriately to subsequent data, given this training data. Each event had different number of labels and the training data was EEG data beginning 150ms before the time of event until 100ms after the event.

- *Cross-Validation*

To improve both the robustness of the classifiers and their ability to generalize to new data, five-fold (leave-one-out) cross-validation was used. This process reduces the likelihood of erroneous results, as multiple splits of the data are considered. Cross-validation was performed on data from each event by dividing the data into five splits. We then iterated through five separate LDA models – each training on four of five trials. The remaining fifth trial was then used as a blind test. As we iterated through the cross-validation, each trial was used once as a test data. Classification test results then came from the accuracy on classifying the respective unseen fifth, and the score was averaged across the five splits. All classification results reported are from this average of all five cross-validation splits.

- *Decision Analysis*

The last process or component of any EEG authentication system is decision making. Based on the matching score generated from the classification process, this component is responsible for making decisions either accepted or denied. After collecting a new pattern of brain activities, it is analysed in order to identify activities performed by the potential owner. A comparison between the newly acquired patterns is compared with the already known and saved one and the distance between the two patterns is calculated, with the final decision of the EEG authentication system being made based on the smallest distance reached between the two patterns (Gui et al., 2015).

- *Performance Metrics*

The success of a classifier can be given simply as percent-age correctly classified. This can be valid in many contexts, but does not clearly show that performance depends on both 'sensitivity' (true positives) and 'specificity' (true negatives). A receiver–operator characteristic (ROC) plot *(Hand, 2009)* illustrates both sensitivity and specificity – with the area under the curve (AUC) of the ROC of 0.5 signifying random chance prediction and one being perfect prediction. This was relevant here as over 60% of data in both training and test situations belonged to the '7' and '8' event class. If a classifier were to predict 'object absent' everywhere, it might get 92% accuracy despite conveying no useful information. AUC, however, would correctly score that classification as no-better-than-chance performance. Plotting a ROC curve can be particularly useful when sensitivity and specificity are being manipulated separately, but here area under this curve (AUC) is simply used as a concise metric of both classifier sensitivity and specificity.

Linear Discriminant Analysis (LDA)

LDA is one of the linear classification methods that require less examples in order to obtain a reliable classifier output. In LDA, assumption is made that each data element s_i has m features and the number of examples is n where each example is assigned to one of the two classes $C = \{0, 1\}$. Then S is a matrix of size n, X m, and C is a vector of size n. N_0 and N_1 are the number of elements for class 0 and 1, respectively. The mean c_m of each class c is the mean over all s_i with i being all elements within class c. The total mean m of the data is

$$\mu = \frac{N_0\mu_0 + N_1\mu_1}{N_0 + N_1}$$

The covariance matrix C of the data is the expectation value for

$$C = E < (s-\mu)^T (s-\mu) >$$

Then, the weight vector w and the offset w_0 are

$$w = C^{-1}(\mu_1 - \mu_0)^T$$

$$w_0 = -\mu w$$

The weight vector w determines a separating hyperplane in the m-dimensional feature space. The normal distance $D(x)$ of any element x is

$$D(x) = xw + w0$$
$$= (x - \mu)w$$
$$= (x-\mu)C^{-1}(\mu_1 - \mu_0)^T$$

Implementation, Result and Discussion

Tools Used

Matlab programming language was adopted in this project because it allows matrix manipulations, plotting of functions and data and it also allows implementation of algorithms. Various Matlab-based toolboxes are used in this project based on their abilities to perform EEG processes required in this work.

SEREEGA (A modular open source Matlab – based toolbox is used to generate Event related electroencephalography (EEG) data used in this project. SEREEGA functions are called in a Matlab script and values were assigned to variables in the script to simulate the EEG data used in this project.

The BCILAB toolbox in MATLAB is then used as the main interface for all the subsequent analysis and mode modelling and analyzing of the EEG data is done

Operation of the Model

The model is developed on BCILAB toolbox in Matlab and it provides a good opportunity for analysis of a new data using the model. Once the model is loaded into the BCILAB interface, new data can be loaded or streamed for classification with the model and the result of the model is clearly visible. Depending on the result of the EEG data, the user that owns the data can be denied access into any system that is using the model

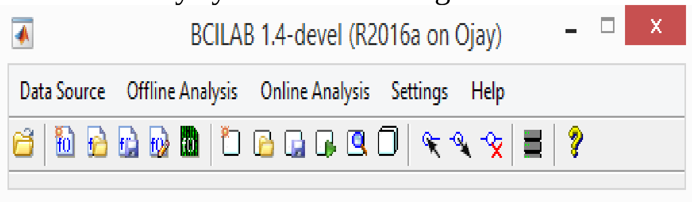

Fig 4.1 The BCILAB interface where the EEG model is created and used

The BCILAB interface is shown below with much functionality. By clicking on the Data source, EEG recording can be loaded. Then clicking on offline analysis, options are displayed which allows you to select and edit an approach that you want to use for the modelling. After the modelling is successful then it is saved. The model can be loaded later to be applied on new data and then the result is displayed

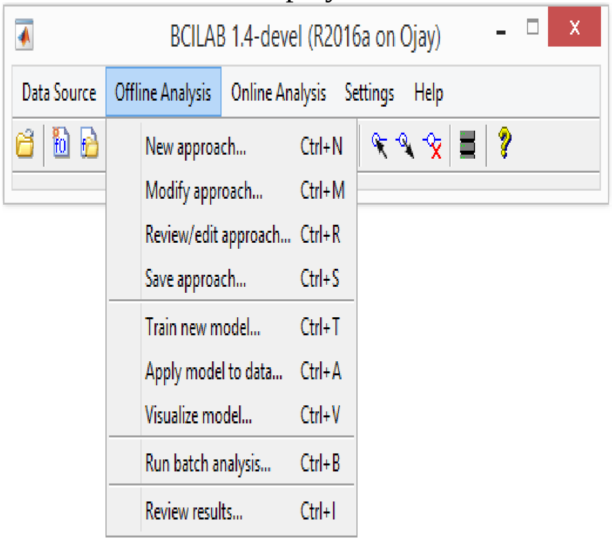

Fig 4.2 BCILAB Interface for the modelling

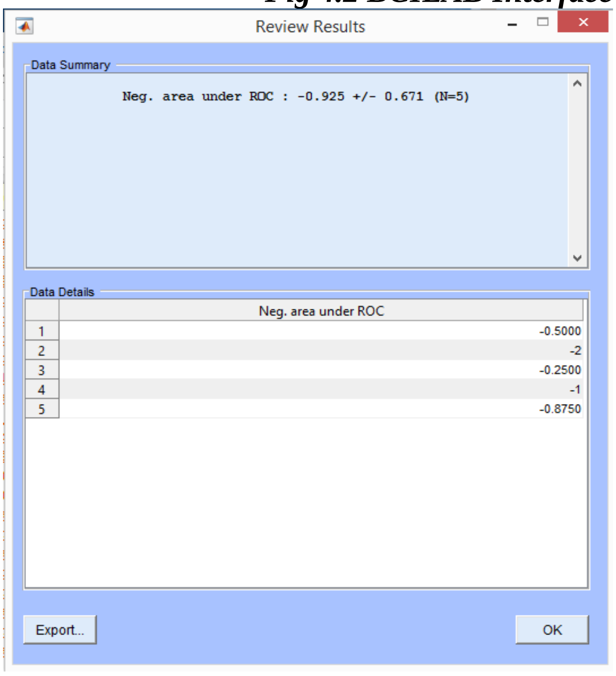

Fig 3.3 Model classification results

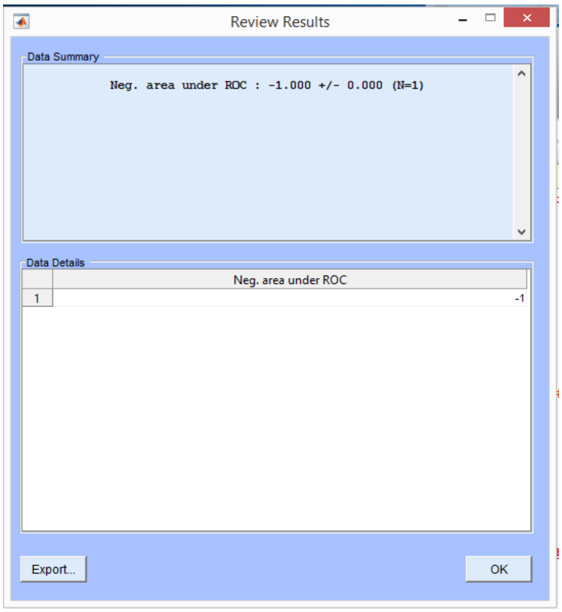

Fig 4.3 Model result when applied to EEG data

CONCLUSION AND FUTURE WORK

Brain activity-based biometrics is the best replacement for other types of biometrics. In EEG systems, authentication problems in other biometric systems are absent but it does not monitor what happens after a user is authenticated/granted access to use a system hence the development of Human doubt model that enables continuous authentication of users after access has been granted to them and this will enable any system achieve perfect accuracy and effectives in the access control of computing resources.
In the future, we plan to continue the study on human doubt modelling and its integration into security/access control systems.

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