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Emotion recognition from EEG using Matlab

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Abstract - Our brain state is affected by and adapted to our surroundings. Therefore, to study natural states of the brain, it is desirable to measure brain responses in natural environments outside the lab. Among functional brain scanning methods, electroencephalography (EEG) is the most promising method for non-invasive brain monitoring in real-life environments. To enable long-term recordings in real-life, EEG devices must be wearable, user-friendly, and discreet. Ear-EEG is a method where EEG signals are recorded from electrodes placed on an earpiece inserted into the ear. The compact and discreet nature of an ear-EEG device makes it suitable for long-term real-life recordings. In this study, 3 to 5 subjects were recorded with conventional scalp EEG and ear-EEG. All recordings were performed with the same instrumentation and paradigms in both a lab setting and a real-life setting. The ear-EEG recordings were performed with a previously developed dry contact ear-EEG platform. In this research, an emotion recognition system is developed based on valence/arousal model using electroencephalography (EEG) signals. EEG signals are decomposed into the gamma, beta, alpha and theta frequency bands using discrete wavelet transform (DWT), and spectral features are extracted from each frequency band. Principle component analysis (PCA) is applied to the extracted features by preserving the same dimensionality, as a transform, to make the features mutually uncorrelated. Support vector machine (SVM) and artificial neural network (ANN) are used to classify emotional states. performs with 91.3% accuracy for arousal and 91.1% accuracy for valence, both in the beta frequency band. Our approach shows better performance compared to existing algorithms.

***Key Words*:** EEG,PCA,DWT,ANN,SVM

1.Introduction

The German psychiatrist Hans Berger in 1924 recorded for the first-time electrical activity in humans by means of electrodes attached to the scalp and a galvanometer. In 1929, and despite the rudimentary tools and devices at the time, he was able to describe some low-frequency oscillations that he called Alpha waves. After these milestones, the principles and basic procedures of electroencephalography (EEG) have barely changed.

In the EEG acquisition, the preparation time is a laborious process that begins with the localization of sites for the electrical montage. Then, and in order to decrease the skin impedance to acceptable values below 20 KΩ, these locations are rubbed with an abrasive paste that removes part of the outer skin, otherwise called stratum corneum (SC) which is the major contributor to the skin impedance. Then, popular Ag/AgCl electrodes are impregnated with an electrolyte gel that facilitates the transduction of the ionic currents, which freely move through brain tissues and the cerebrospinal fluid, into electric currents. Furthermore, the electrode-skin impedance must be measured to guarantee a low value.These are mainly hands-on tasks that require staff with expertise in EEG. Another remarkable inconvenience is the annoyance caused to the subject under test. Once an acceptable electrode impedance has been achieved, a countdown begins until the gel dries, thus causing the transductive properties to disappear. For these reasons, wet electrodes are not suitable for long-term measures.

In recent decades, there have been several approaches to develop dry electrodes based on micro electro-mechanical systems (MEMS), non-contact, capacitive, etc. These approaches, when combined with the new generation of on-site low energy instrumentation amplifiers, enable the development of portable, active and dry electrodes in a back-to-back design. Therefore, dry and active electrodes seem to be the solution to the disadvantages of wet EEG electrodes. However, these new technologies must be conveniently evaluated and validated before use.

2. Literature Review

The electroencephalogram (EEG) is a classic non-invasive method for measuring a person's brainwaves and is used in a large number of fields: from epilepsy and sleep disorder diagnosis to Brain-Computer Interfaces (BCI)[1]. Current portable EEG systems, however, still have a number of drawbacks principally related to their cumbersomeness and ease of use. Wearable EEG is envisioned as the evolution of ambulatory EEG units from the bulky, limited lifetime devices available today to small devices present only on the head that can record EEG for days, weeks or months at a time. Such miniaturized units could enable prolonged monitoring of chronic conditions such as epilepsy[11], and greatly improve the end user acceptance of BCI systems. Results presented here from a questionnaire of neurologists indicate that there is a medical interest in the development of wearable EEG systems. Given these results, this article overviews the application areas for wearable EEG systems, and highlights the current research challenges still remaining: the development of new electrode technologies and lower power consumption electronics. In particular, techniques for reducing the battery size needed to power the portable EEG unit, while simultaneously increasing the operational lifetime, are investigated. This is done by considering the trade-off between the use of online data compression, the desired physical battery size and the power budget available for implementing the compression[2]. For systems where the power consumption is dominated by a wireless transmitter stage, using a small amount of power to compress the raw EEG data in real-time can lead to a much larger reduction in the overall system power consumption. Modelling work presented here allows this effect to be quantified, and sets the power budget available for the online implementation of a

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given compression algorithm.A problem inherent to recording EEG is the interference arising from noise and artifacts. While in a laboratory environment, artifacts and interference can, to a large extent, be avoided or controlled, in real-life scenarios this is a challenge[3].

2. Proposed System

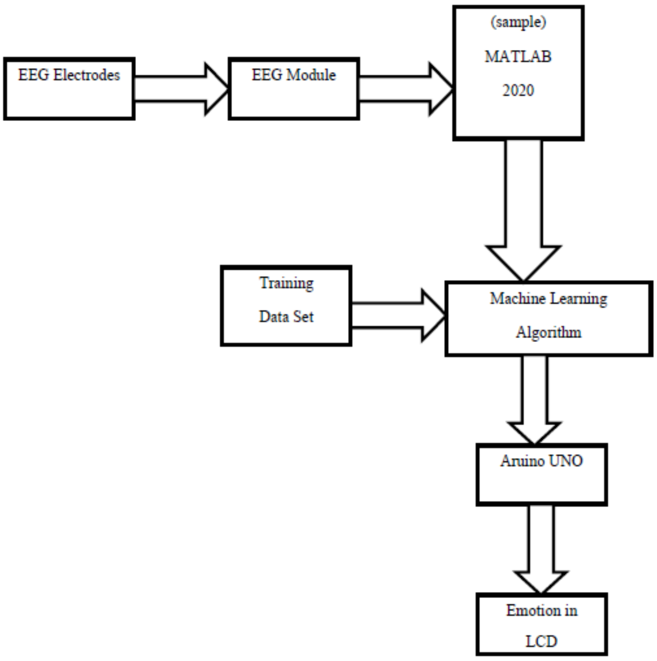

Fig 1. Block Diagram of the Proposed System

In this project,the EEG Module with dry electrodes (from Mind wave company) is used. EEG signal from the brain is used to generate a Brain-Computer Interface (BCI) through Bluetooth HC-05.The output acquired from the EEG Module,is sent serially to the Computer. EEG data is processed using Matlab software.The EEG signals are collected and preprocessed using special filters and features are extracted. The EEG signal is time domain signal and the signal energy distribution is scattered. In order to extract the features, the EEG signal is analyzed to give a description of the signal energy as a function of time and frequency. The features extracted in frequency domain can recognize the mental tasks based on EEG signals. The analysis method applies DWT to the signal and find out its spectrum. EEG signal is non-stationary that means its spectrum changes with time. Such a signal can be approximated as piecewise stationary, a sequence of independent stationary signal segments. Although the field of spectral analysis has been dominated by use of the Fourier transform, which do not adequately represent non-stationary signals, the filter process through feature extraction with PCA and classification via SVM and ANN are performed**.**The classified output of the emotional state in sent serially via Arduino and finally displayed on the LCD.

3.Results And Discussions

The project is implemented using MATLAB Software.A Gui interface is designed as shown in the Fig.2 given below.

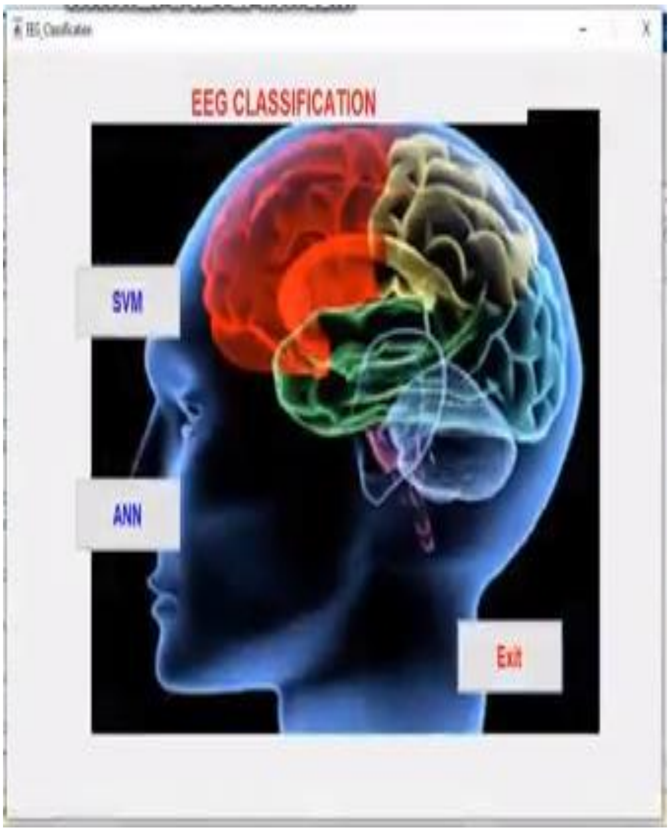

Fig 2. GUI Interface for EEG Classification

The raw signal that has been extracted from the electrode is plotted as shown in the Fig 3.

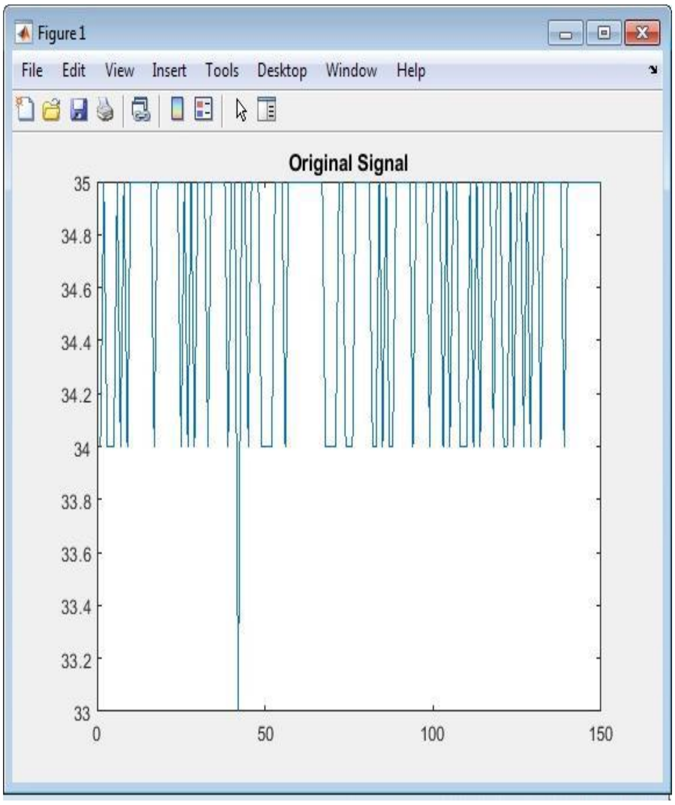

Fig 3. Extraction of the Original Signal

The raw dataset was created for various mind states such as concentration state and exercise state.The EEG electrode is connected to the head and the person is made to concentrate and the signals are recorded and stored in an excel file as shown in the Fig.4.

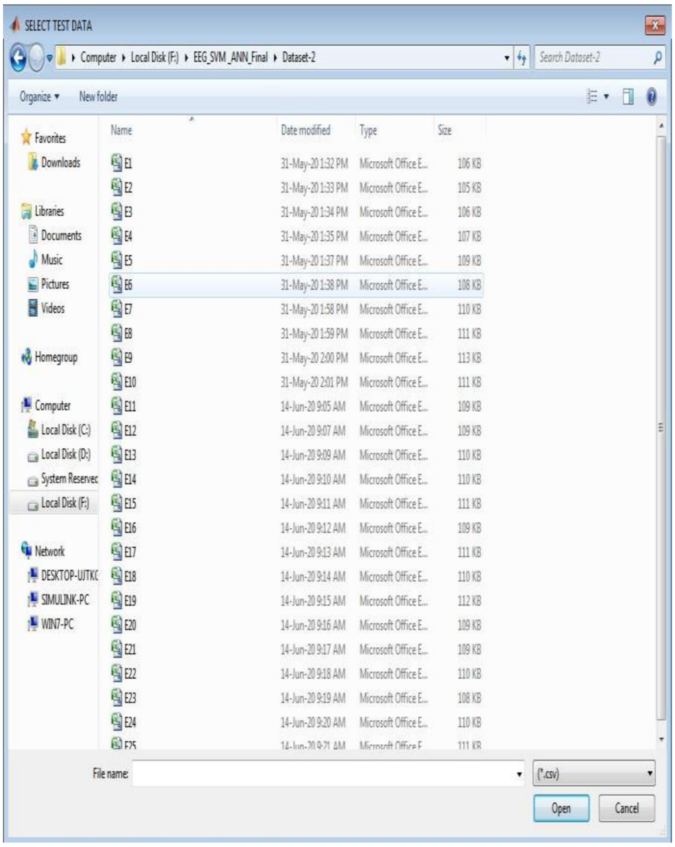

Fig 4. Dataset created for Concentration State

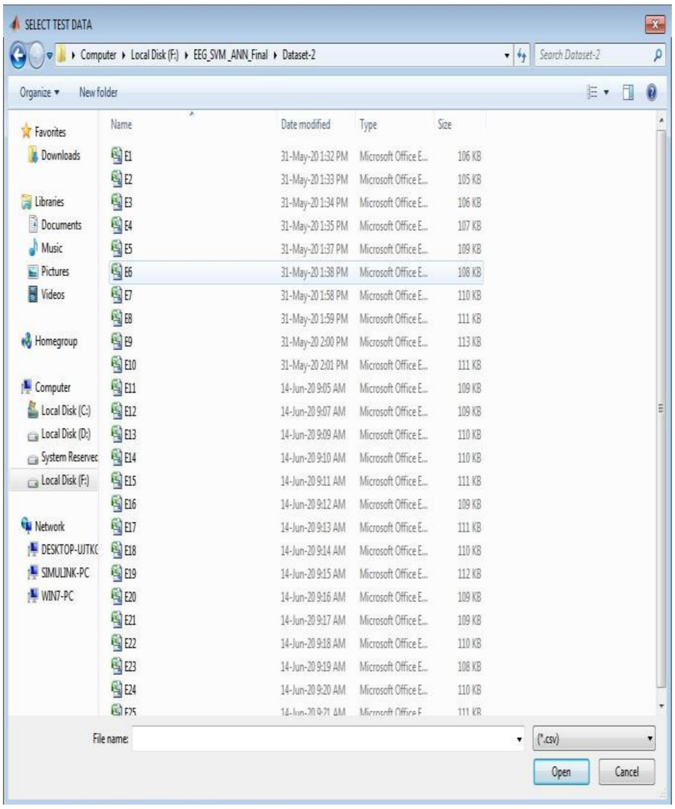

Fig 5. Dataset created for Exercise State

Next the person is made to do exercise and the signals are recorded and stored in an excel file as shown in the Fig.5.A total of 25 samples of each state are prepared for training the dataset.A live data as shown in the Fig.6 is taken for testing the dataset by making the person concentrate.

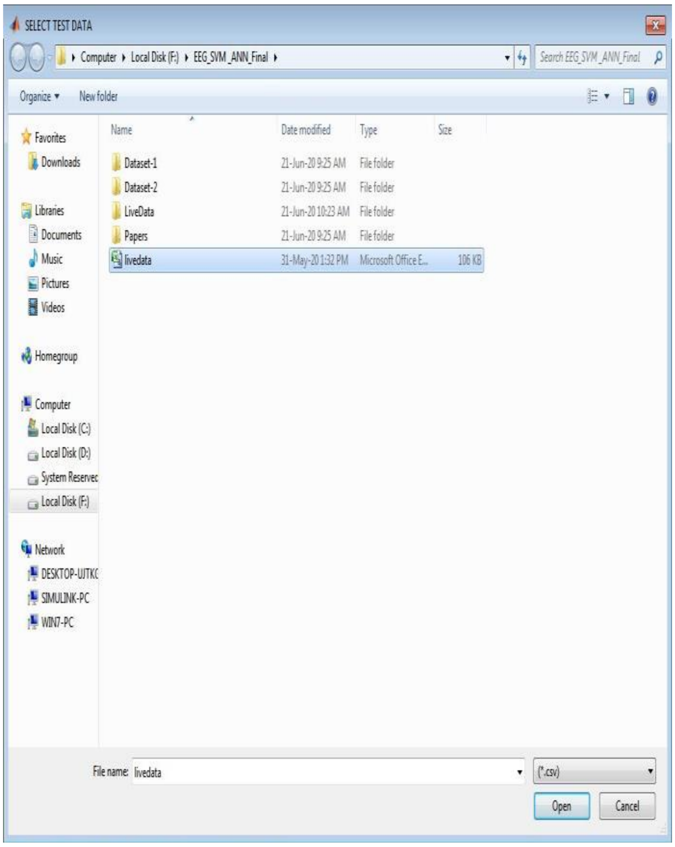

Fig 6. Sample Live Data taken for Testing

For pre-processing of the EEG Signal,DWT and PCA are applied for Feature Extraction.Then by implementing SVM Classifier Algorithm the obtained result is shown in the Fig.7

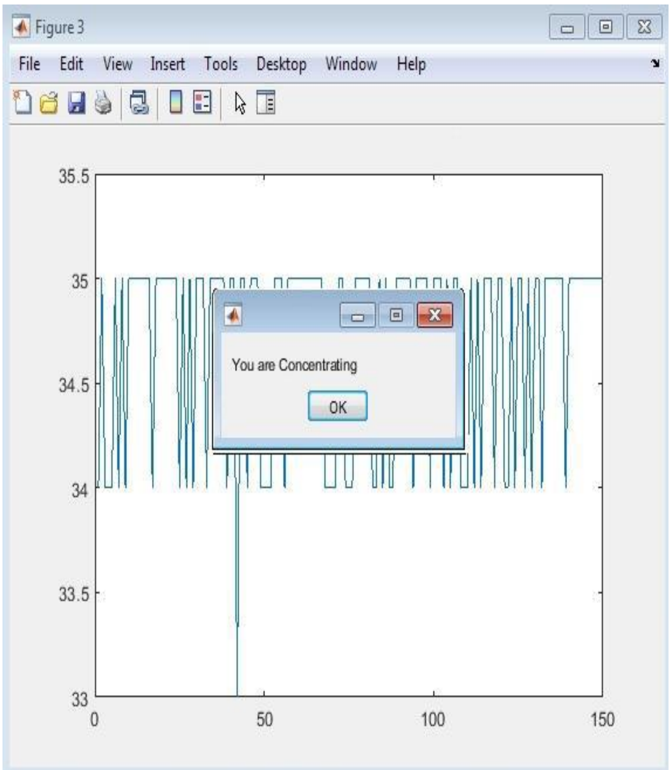

Fig 7. Output of the Live Data Tested using SVM Classifier

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Next Exercise Live data is taken for Testing using ANN Algorithm.The Original raw Signal for exercise state is shown in the Fig 8.

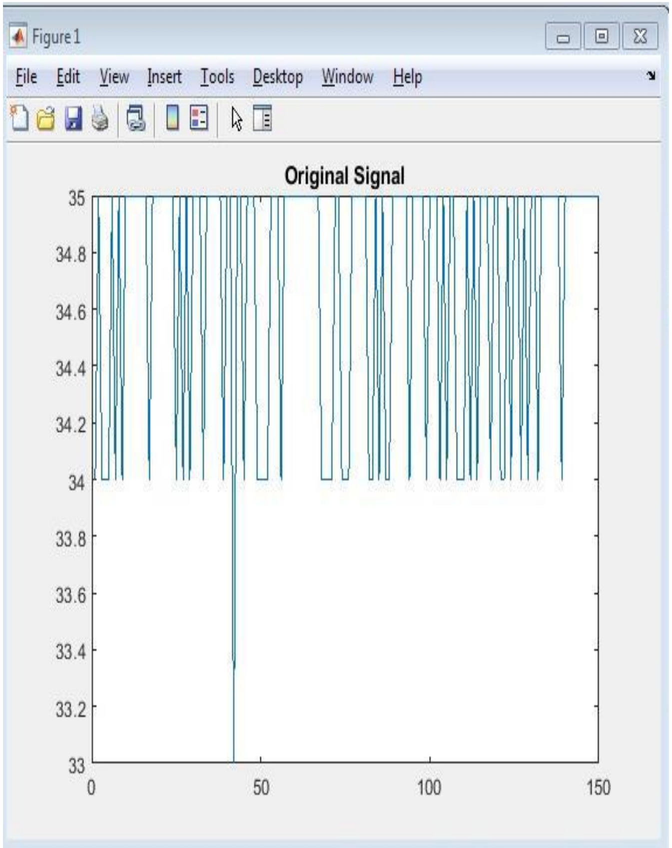

Fig 8. Original Signal of Live Exercise Data Taken for Test

The ANN Classifier applied for Training and Testing the dataset are shown in the Fig 9.below.

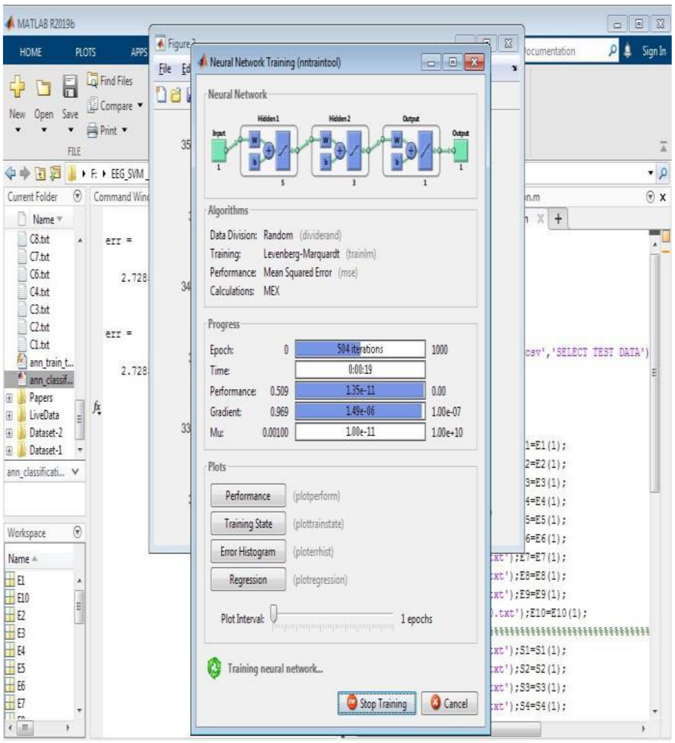

Fig 9. Training and Testing the Dataset using ANN Classifier

The Output of the Live data tested using ANN Classifier is shown in the Fig 10.

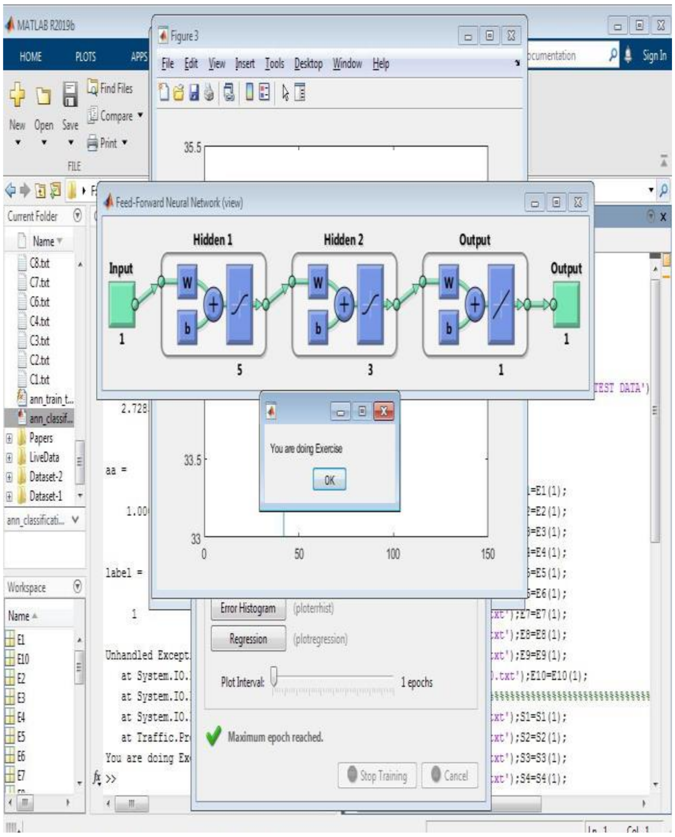

Fig 10. Output of the Live Data Tested using ANN Classifier

3.2 Sensitivity

It is defined as the number of true positive decisions(TPR) made by the classifier.

$$TPR = \frac{TP}{TP+FN} X\ 100\%$$

From the total output of ten subjects, the sensitivity was calculated to be 85% with SVM classifier and 100% with ANN classifier.

3.3 Accuracy

It's the ratio of number of correct decisions to total number of cases. From the total output of ten subjects, the accuracy was calculated to be 85% with SVM classifier and 96% with ANN classifier.

3.4 Advantages

- Dry-EEG electrodes do not require the use of any substance, making contact directly with the scalp.
- They are fast to place, comfortable to wear, do not require the head to be cleaned after usage, and do not require heavy hygienic procedures on the equipment afterward.
- Real-life monitoring of ear-EEG using dry electrodes enable research of evoked responses and spontaneous responses related to everyday life situations.

- DWT has a varying window size, being broad at low frequencies and narrow at high frequencies and is better suited for analysis of sudden and transient signal changes as is the case of EEG signals.
- PCA is used as EEG has large number of variables and there occurs some redundancy in these variables.
- ANN classified the EEG signal having accuracy 96% and sensitivity 100% for wavelet feature extraction.
- SVM classifier achieved accuracy 85.46% and sensitivity 90% for wavelet feature extraction.

3.5 Disadvantages

- The use of some dry electrodes could not be extended beyond certain specific applications (e.g., Alpha-BCIs or SSVEP-BCIs, respectively).
- The high contact impedance between sensor and the skin requires the sensor and amplifier layers to have higher performance and more sophisticated features so as to be able to deal with more noise and artifacts.
- Selection of a proper mother wavelet is necessary for proper operation of DWT
- PCA also performed more poorly at extracting non-brain artifact sources from EEG data.
- A drawback of SVM is the problem complexity which is not of the order of the dimension of the samples, but of the order of the number of samples.
- Learning in ANNs is accomplished through special massively parallel training algorithm.

3.6 Applications

The real-time EEG-based emotion recognition can be applied to many fields such as entertainment, education, medicine, etc. The user emotions are recognized and visualized in real time on his/her avatar adding an ―emotion dimension‖ to human computer interfaces. In the communication of human-machine-interaction, emotion recognition will make the process more easy and natural. Another example, in the treatment of patients, especially those with expression problems, the real emotion state of patients will help doctors to provide more appropriate medical care. In recent years, emotion recognition from EEG has gained mass attention. Also it is a very important factor in brain computer interface (BCI) systems, which will effectively improve the communication between human and machines. An EEG-enabled music therapy may be implemented. Music therapy is considered as a nonpharmacological intervention to help the patients deal with the stress, anxiety and depression problems. This method also provides a positive support in the treatment of the patients suffering from Alzheimer's disease. Their anxiety levels can be determined and suitable therapy sessions may be provided.

4. Conclusions

In this study, emotion classification using newly proposed energy features are presented. Here, the modified energy features gives the maximum average classification rate over other conventional features. Therefore the extracted features successfully capture the emotional changes of the subject through their EEG signals regardless of the user's cultural background, race, and age. In addition, it also shows a significant relationship between EEG signals and emotional states experienced by the subjects during the interaction with audio-visual content. This study is ongoing to involve different classification algorithms in order to track the emotional status of brain activation during audio-visual stimuli environment. The results of this study provide a framework of methodology that can be used to elucidate the dynamical mechanism of human emotional changes underlying the brain structure. Based on the study, it is concluded that dry-contact electrode ear-EEG is a feasible technology for emotion recognition from EEG recordings.

5. Future Scope

An EEG-based web-enable music player which can display the music according to the user's current emotion states can be designed and implemented. For future works, other transforms such as independent component analysis (ICA) or linear discriminant analysis (LDA) could be applied, on the extracted features.Also more strategies such as feature smoothing and deep network to improve the classification accuracy can be implemented.

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