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EEG SIGNAL ANALYSIS BASED WIRELESS SAFETY HELMET MOBILE APP

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ABSTRACT— The recent technology in digital computing created many ways of drowsiness detection. This is important because of the increased numbers of accidents caused by drowsy drivers. In this paper, an approach for detecting drowsiness state by continuously analyzing EEG signals is proposed. Using a single dry-sensor EEG headset, a real-time system that monitors and analyzes the EEG signal of the driver is developed. It automatically produces an alarm to alert the driver via an Android mobile application in case of detecting stage-one sleep. In addition to being portable, the system reached an average accuracy of 97.6% with a low false positive rate in a sample of 60 subjects using the statistical characteristics of the EEG waves.
Keywords—drowsiness detection, EEG classification, neural networks, mobile app

I. INTRODUCTION

Driving for a long period causes excessive fatigue and tiredness; these in turn make the driver sleepy or lose awareness [1]. With the rapid increase in the number of accidents daily, the need arises to design a system that not only keeps the driver focused on the road but also alerts him before falling into sleep while driving. This system has to be an affordable, reliable, real-time and easily used. Our goal is to develop a system that can be used as a medical mobile app. Mobile applications are everywhere, the buzz around mobile apps extends from the pages of the newspapers to of course, the screen of our phones. A mobile app is a computer program designed to run on smartphones, tablet computers, and other mobile devices.

Apps are usually available through application distribution platform. This began appearing in 2008 and is typically operated by the owner of the mobile operating system, such as the Apple App Store, Google Play, Windows Phone Store, and BlackBerry App World. Usually, they are downloaded from the platform to a target device, but sometimes they can be downloaded to laptops or desktop computers. Mobile apps originally offered for general productivity and information retrieval, including email, calendar, contacts, stock market and weather information. However, public demand and the availability of developer tools drove rapid expansion into other categories, such as those handled by desktop application software packages. As with other software, the explosion in

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number and variety of apps made discovery a challenge. That in turn led to the creation of a wide range of review, recommendation, and certain sources, including blogs, magazines, and dedicated online app discovery services. In this paper, a mobile app for detecting the driver's fatigue is proposed. The proposed technique depends on using the recorded signals from the scalp electrodes that measure electrical activity in the brain during different awareness states. The process of recording these signals is known as Electroencephalography (EEG) [2]. The EEG has four main types; they can be classified according to its frequency. These types include:

 Delta: has a frequency of 4Hz or below. It tends to be the highest in amplitude and the slowest waves. It is detected during deep sleep.

Theta: It has the frequency range from 4Hz to 7Hz. It is detected during slight sleep.

 Alpha: It has the frequency range from 8Hz to 12Hz. It is detected during relaxation and closing the eyes.

Beta: It has the frequency range from 13Hz to 30Hz. It is detected during alert, active and busy status. When the eyes are closed, Alpha waves are detected. Thus to detect a driver's fatigue, his EEG patterns are expected to change from Beta to Alpha waves. In the last few years, toys that have been designed for entertainment purposes have the ability to detect simple EEG signals. These devices use a single dry-electrode to record the EEG signal [3]. That, of course, is different from the EEG medical devices use multiple electrodes, to record EEG signal at multiple locations from the subject's scalp [4], [5]. These EEG headsets are comfortable, and they offer simple EEG recording capability. That is why we used them in our experimental study. One such EEG headset is the NeuroSky mobile brainwave starter kit [3]. In the proposed approach, we continue our previous work with the Neurosky mind wave that the EEG signals were collected with. Then features were extracted, and classified. The proposed approach has proved its efficiency in the context of drowsiness detection. The rest of the paper is organized as follows. Section II presents a review of related research. In Section III, the proposed approach is presented in detail. Section IV presents results and discussions. Finally, the conclusion is presented in Section V.

II. RELATED RESEARCH

EEG has been clinically used to monitor driver and pilot drowsiness [4], [5]. However, these EEG devices are impractical for everyday driver drowsiness detection because of the use of medically grade expensive equipment that needs specific conditions and preparations for effective monitoring [3]. Recently, many studies are performed trying to design systems that can detect the drowsiness of a driver while driving in real time. For instance, a study was made to design and test real-time stage one sleep detection and warning system using a single dry-sensor EEG headset [3]. Stage-one sleep is indicated when the amplitude of the signal transmitted is low, and signal power at higher frequencies has been attenuated. When the EEG transitions resemble that of stage one sleep, the device produces an auditory alarm. The system proved 81% effective in detecting sleep in a small sample group. In 62% of the cases, stage-one sleep was detected after an average of 8.4 seconds. In 19% of the cases, the sleep algorithm indicated sleep in 30 seconds to 20 minutes before stage 1 sleep was indicated. This system has a risk of high false alarm rate (up to 14%) and a limited number of test subjects (only 16). Also, the test was not performed on sleep-deprived subjects who were trying to stay awake.

People are using their mobile phones while driving, especially texting, also called texting and driving. It is the act of composing, sending, reading text messages, email or making other similar use of the web on a mobile phone while operating a motor vehicle. Texting while driving is considered dangerous by many people, including authorities, and in some places has either been outlawed or restricted. An American Automobile Association study showed that 47% of teens admitted to being distracted behind the wheel because of texting and 40% of American teens say they had been in a car when the driver used a cell phone in a way that put people in danger [6]. A study involving commercial vehicle operators conducted in September 2009 concluded that though the incidence of texting within their dataset was low, texting while driving increased the risk of an accident significantly [7]. The scientific literature on the dangers of driving while sending a text message from a mobile phone is limited but growing. A simulation study at the Monash University Accident Research Center provided strong evidence that retrieving and, in particular, sending text messages has a detrimental effect on many safety-critical driving measures [8]. That means instead of falling asleep the driver loses his attention of the road. In this case, the drowsiness detection systems will lose its advantage as the driver will be focused but not on the road, and the system will not be effective.

Our main goal is to prevent the accident by any means necessary. Therefore, by extending our system into a mobile app, we are hitting two birds with one stone, because when the system is used as a mobile app the driver will not be able to use his mobile while driving. That will raise the chances of paying attention to the road and making the driver focus on the road, as he cannot use his mobile. Previously, an effective low-cost EEG classification technique for detecting drivers' drowsiness and alerting them in real time was proposed [9]. The presented approach employed Neurosky Mindset, which is an EEG device using a single dry-sensor electrode that can be mounted at position Fp1 on the forehead. It also uses an ear clip for grounding. The Neurosky Mindset is shown in Fig. 1.

Figure 1. Neurosky mind wave [3]

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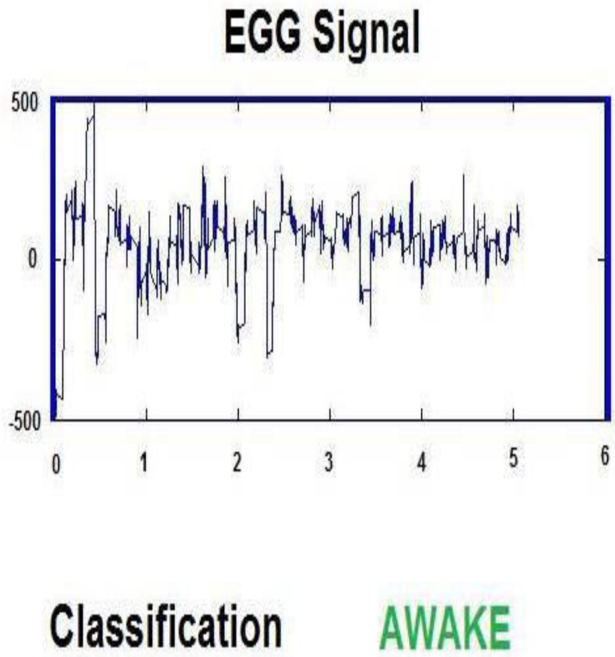
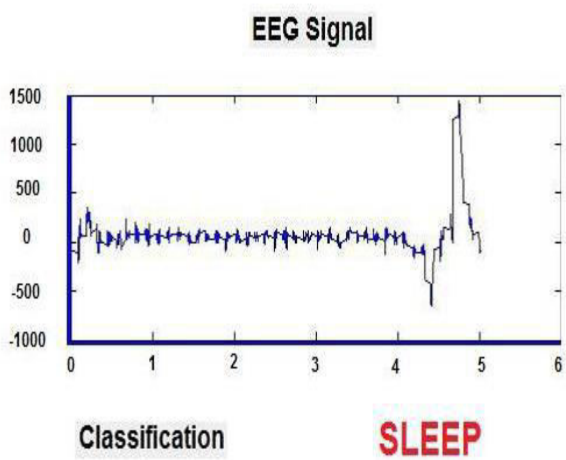


(A)



(B)

Figure 2. The automatic classification system: A) the case of the awake condition, B) the case of sleep condition [9]

III. PROPOSED APPROACH

In this paper, a mobile-based application fordetecting drowsiness while driving is proposed. The Neurosky mobile mindset, which is shown in Fig. 3, will be used in this system.

Figure 3. The Neurosky mobile mindset [10]

The proposed approach consists of two stages as following below.

A. Offline Detection System

The offline system consists of five steps as shown in Fig. 4.

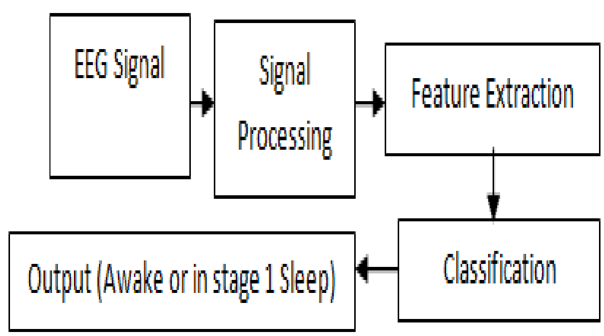


Figure 4. Block diagram of the training phase

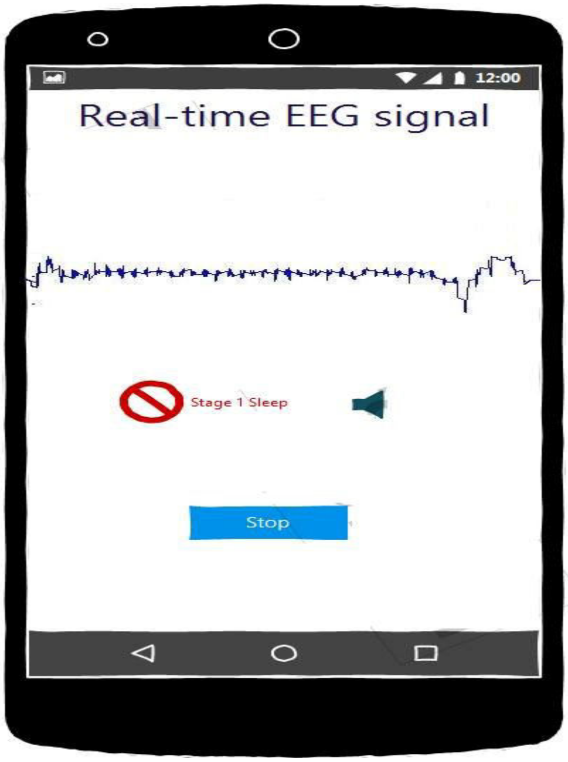
In the first step, the initial data were collected by using the Neuroview software, which allowed us to record a single channel EEG signal. It produces a .CSV file which is then read into MATLAB. The used dataset was collected from 60 subjects with ages between 20 and 50 years and consists of 600 raw wave EEG signals. In the recording phase, ten different signals from each subject in different awareness conditions were recorded. Moreover, from each subject, we took five awake normal EEG signals while driving, and another five signals while the subject was drowsy (not sleeping for 24 hours) while driving under good observation. Thus, we had 10 EEG recordings from each subject that made a dataset of 600 signals divided into 300 awake signals and 300 sleep signals with different times from 10 seconds to over 1 minute long. Then, the collected signals were divided into 400 signals for training and 200 signals for testing. Moreover, for the processing step, these EEG raw wave signals are processed with the MATLAB to extract the features that can differentiate between awake and sleep. The processed raw waves consist of 512 samples multiplied by the number of seconds for each record that gave us an array of numbers to extract the features. In this step and according to the previous work [9], we did not use the frequency-based features which includes; the Power Spectral Density (PSD) amplitude of the Fourier transform of the signal within the period from 1Hz to 30Hz as frequencies from 1Hz to 16Hz increase during fall into sleep while frequencies from 17Hz to 30Hz increase during the awake condition. Instead, we used the statistical features as they gave us the best accuracy. These include; the maximum and minimum values of each signal, mean values, standard deviation, and the median values.

For the classification step, a neural network classifier with back propagation is used to classify awake and stage-one sleep classes. We specially used the neural network classifier as it has been widely used in many medical applications like leukemia classification [11], automatic diagnosis of liver diseases [12], and diagnosis of cardiac arrhythmias [13], protein classification [14] and many other applications [15]-[21]. The network has three layers; the first one is the input layer that has 5 neurons, the second layer is the hidden later with 20 neurons, and finally, the third layer is the output layer that has 1 neuron. The output is decoded as 0 to represent sleep and 1 to represent awake.

B. Online Android Application

By using Developer Tools 3: Android and Android Studio 1.2.1.1 [22], we were able to create Mind Wave Mobile compatible Android application that could sense the users' brainwaves and compare these waves with stored default collected data from the offline detection system. Thus, a continuous monitoring of the signal is performed. Each one second the system displays the captured EEG signal and makes the analysis and classification. And because the classification depends on only five statistical features, the processing is done in no time. So, after this one second, if the captured signal is classified as awake, the system displays the result and repeats the process, and if the captured signal is classified as sleep, the system displays the result and produces a loud alarm for 20 seconds to alert the driver and repeats the process and so on. Fig. 5 shows the two conditions of the system.

(A)



(B)

Figure 5. The system as a mobile app: A) the case of the awake condition, B) the case of sleep condition

IV. RESULTS AND DISCUSSION

In this section, results and analysis of the proposed approach is presented. Table I shows the set of features that were used in the feature extraction step. The best accuracy was given when we used a set of statistical time-domain and frequency domain features. Details on the experimental setup and the obtained results are found in [9].

Table i. The relation between the accuracy and,theusedfeatures

Used Features	Accuracy %
Statistical Features	97.3
Frequency based feature	93
Mix between statistical and frequency based features	95

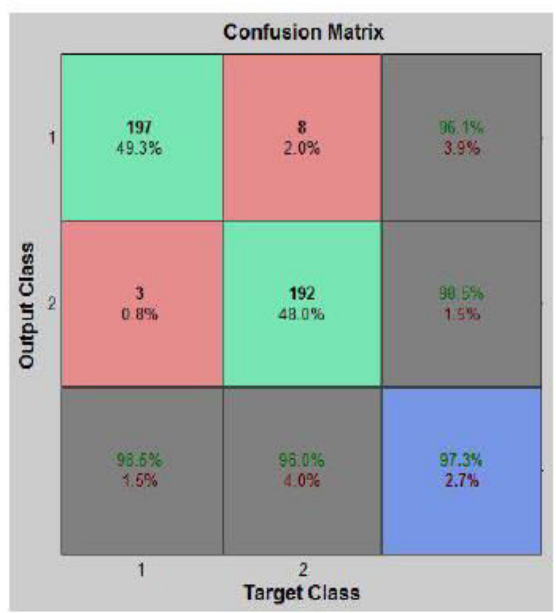


Figure 6. Confusion matrix

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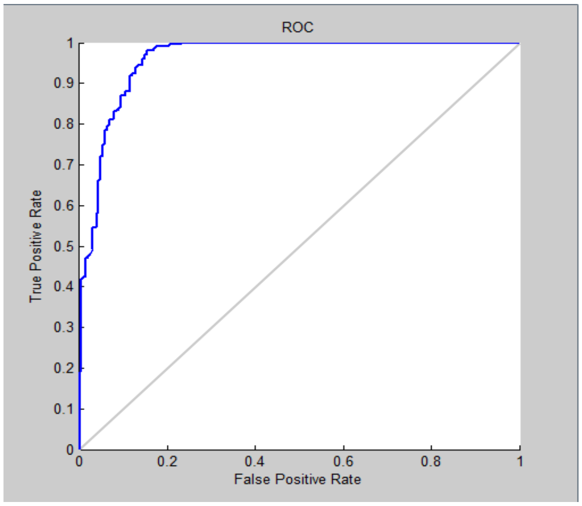

Figure 7. ROC curve

The output of the classifier in the training and testing phase for the first direction of work is shown in Fig. 6. In this figure, class 1 denotes the awake signals; meanwhile class 2 denotes the sleep. As shown in the figure, the classification accuracies for awake and sleep are 98.5% and 96% respectively. Thus, the average accuracy is 97.3%. Also, the false positive rate is 2% which is acceptable in this context.

The ROC curve is shown in Fig. 7. It shows that the used classifier has good performance since the curve almost touches the perfect performance point in the top left corner. As presented in the previous analysis, the proposed system is effective since it yielded an acceptable accuracy. Also, it is affordable, real-time, and portable.

V. CONCLUSION

In this paper, an efficient system for the classification of EEG to predict drivers' drowsiness system mobile app is presented. The obtained average classification accuracy is 97.3% in real time with a low false positives rate. The proposed system has the following advantages in comparison with similar approaches. First, it is highly-affordable as it employs only one electrode, it is lighter in weight than the ordinary EEG devices, and less expensive. Second, the proposed system which is less complex as the classifier uses only five well-discriminating features between awake and sleep signals which minimizes the analysis time. Third, the system is mobile-based which makes it portable and available everywhere easily.

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