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PRIMARY RESEARCH

Framework for modeling of regaining the attention

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Abstract— This research purpose was to identify attention as the primary characteristic of mindfulness, among other cognitive features. The utility of training attention is evident in real-life situations such as listening to others, driving a car, conducting a medical-surgical procedure, and so forth. Therefore, we argue that devising a method for detecting the moment at which the attention is distracted would be beneficial to the cultivation of attention. We have conducted research to develop a software framework that can model attention pertaining to a particular task and give an alert when attention is distracted. The framework has been designed to capture attention-related Electroencephalography (EEG) brain wave signals in response to a specific task and to train an Artificial Neural Network (ANN). The trained ANN can be used to receive EEG signals during a task and determine an individual's attentiveness. Accordingly, a vibration alert is sent to an individual's mobile phone to serve as a signal for the person to refocus attention. The framework has been used to model attention during a lecture, and an experiment was conducted to assess the attentiveness of students. The experimental results determined that 75% of students were able to maintain attention during a lecture, and vibration alert has been effectively supportive of regaining the attention. Hence, we conclude that our software framework can be used to the model regaining attention in a session that requires the focused attention.

I. INTRODUCTION

With the increasing popularity of Artificial Intelligence (AI), numerous intelligent techniques including Artificial Neural Networks, Genetic Algorithm, Expert Systems and Agent Technology [1] have enabled the development of intelligent software solutions for real world problems which could not be solved otherwise. AI techniques have shown their potential in solving problems in mainstream of science, medicine, engineering, and social sciences. In the recent past, AI has also played a tremendous impact on brain mind modeling and simulation [2, 3]. In this context, research in EEG brain waves for mind controlled vehicles [4], games [5] and wheel chairs [6] have recorded exciting results.

In particular, researches have been conducted to study brain wave signals generated under various mental conditions such as emotions, anxiety, and attention regulation. Among others, within the context of mindfulness research, numerous researches have been conducted to study the attention regulation as a key cognitive feature of human mind. In a broader sense, mindfulness is defined as a particular way of paying attention [7]. Thus mindfulness is primarily about attention. Mindfulness or maintaining attention can be taken as the single cognitive feature that

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energizes development of other cognitive features such as retention, thinking, and regulation of emotions. Our lives are full of events where we are required to maintain a high level of attention. For instance, listening to something, following a lecture, reading, driving, counting, and shooting can be stated as some regular activities requiring the maintenance of attention. In such events, people lose attention without noticing the moment at which the mind drifts away from the main theme, and this surfaces the research gap of requiring the detection of this particular moment and supporting the regaining of attention accordingly. Therefore, research into development of a device which detects the moment at which the mind goes away and generates an alert signal to bring the mind back would be of great interest. Accordingly, we conducted a research to develop a software framework which captures EEG brain waves pertaining to attentive and non-attentive sessions and trains an Artificial Neural Network that can assess whether a person is attentive in a particular session. The framework has been used to test for attention regulation in a classroom scenario. According to our experiment, 75% students have been able to regain attention and get back to the lecture with the aid of the alert signal generated by the device. The solution has been developed as a mobile application that can run on a smart phone. The framework developed in this research can be used to model the regaining of the attention lost in any session such as driving, shooting, listening and so on. The development of the solution as a mobile app makes it accessible for a very wide group of users. Undoubtedly, this research will have a greater significance specifically for the worldwide student community for whom maintaining attention in the learning process is of paramount importance.

A. Objective of the Study

The objective of this research is to develop a framework for modeling of regaining the attention lost in a particular session that requires attention.

II. EMERGENCE OF BCI

The Brain Computer Interfacing (BCI) is a relatively new area of research [8, 9]. This field was originally started as an attempt to treat mentally impaired people [6]. However, at present BCI technology has been applied to a wide spectrum of areas such as clinical research, attention monitoring, game playing, entertainment, education, and meditation. The BCI technology primarily uses the EEG wave signals, which are electrical signals generated in the brain due to the firing of neurons pertaining to different kind of activities in the brain. EEG signals are captured by placing electrodes on or near the scalp with a high level of accuracy [10]. Over the last two decades, capturing of EEG wave signals has evolved from wired technology to wireless technologies such as Bluetooth, and the merging of EEG technology with wireless communication has accelerated research in BCI. Nowadays, there are numerous applications utilizing EEG wave signals. Among others, the project by Andersen, Juvik, Kjellen, and Storstein has used EEG wave signals to steer a radio controlled helicopter [5]. With their solution, they have been able to adjust the speed of the rotor using the level of concentration in a test person and lift the helicopter off the ground. Scherer has developed a system [11] for classifying EEG signals using Fisher's Linear Discriminant Analysis (FLDA) and simulating a virtual keyboard for spelling. This identifies left, right and down thoughts. Yaomanee has identified locations on the scalp that are suitable for detecting attention-related EEG signals [12]. This study has shown that when subjects are attentive, β activity in the brain is greater. Large number of EEG appliances are available in the current market [13, 9]. Our study showed that Emotive EPOC and NeuroSky are the most popular EEG appliances that have been used for many researches.

A. Emotive EPOC

Emotive EPOC has been considered as a research grade EEG headset [14]. It provides 14 EEG channels with wireless/Bluetooth connectivity. This appliance comes with wet-sensors, and as a result, usage and maintenance of Emotive EPOC require some additional care. Figure 1 shows an Emotive headset in common use. Emotive EPOC runs with commonly known operating systems such as Windows, Mac, Android and iOS, and currently it costs around $400.

Fig. 1 . Emotive EPOC headset

The Neuro Sky Mindwave is a low cost single-electrode

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EEG headset, and it has been proven effective in detecting user's mental states [15]. It has one dry sensor which is fixed to the forehead area (Figure 2). It supports Bluetooth connectivity and is able to provide raw EEG data. For development purpose, it provides C#.NET API, and its current cost is around $99. This device is compatible with Windows, Mac, Android and iOS. NeuroSky has won much recognition from researchers for general purpose experiments with brain waves.

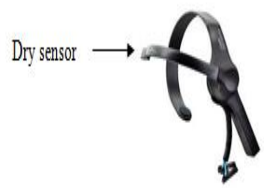

Fig. 2 . NeuroSky mindwave headset

III. FUNDAMENTALS OF EEG AND ANN

A. Electroencephalography

In 1875, Physician Richard Caton discovered the electrical currents in the brain. After 50 years, German scientist Hans Berger proved that weak electrical signals generated by the brain can be amplified and recorded without opening the skull [16]. The finding of Berger marked the birth of EEG technology. In 1934, Adrian and Matthews discovered that the electrical activities in the brain produce the waves in the range of 10-12Hz in regular activities [17] and this research has coined the term "brain wave". Latest developments in EEG technology have offered two major approaches, namely, invasive and non-invasive approaches. An invasive approach requires physical implants of electrodes in humans or animals. In contrast, a non-invasive approach uses Magnetic Resonance Imaging (MRI) and EEG technology to measure brain activities [16].

B. Placement of Electrodes

The positioning of electrodes on the skull to detect EEG signals is a crucial aspect of receiving accurate wave signals from the brain. An international standard for electrode placements is known as the 10-20 system, and shown in Figure 3 [16]. The term 1020 denotes the percentage proportions defined on the skull as shown in the Figure 3.

Electrode placement on the skull is defined with respective areas in the brain: F (frontal), C (central), T (temporal), P (posterior), and O (occipital). The electrodes named with the letters F, C, T, P and Q indicate the EEG wave signals from respective areas of the brain. For example, F7 receives brain waves pertaining to rational activities. Furthermore, Fp1 receives EEG brain waves related to attention. The NeuroSky Mindwave headset with a single sensor has been designed to receive EEG signals from Fp1. T3 and T4 receive signals pertaining to emotional activities, while EEG waves near T5 and T6 are associated with capacity for certain memories. Large collection of literature [8, 13, 9, 16] has described the placements of electrodes on the skull for capturing EEG brain waves.

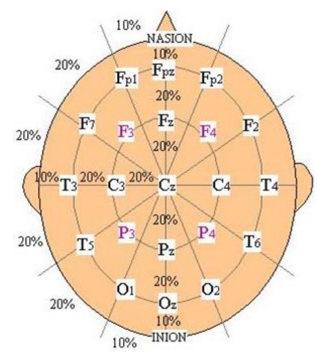

Fig. 3 . The 1020 standard of electrode placement [16]

C. Placement of Electrodes

EEG represents the voltage value generated by actions of neurons in the brain. An EEG signal is a wave similar to one shown in Figure 4. A typical EEG signal comprises of five main EEG frequency bands, namely, α, β, θ,δ and γ [16].

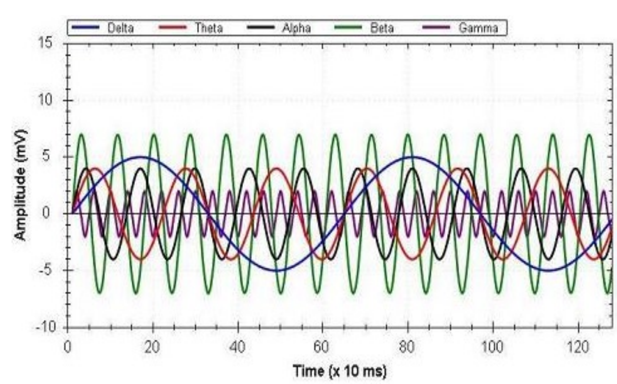

Fig. 4 . EEG wave [11]

The α waves have been identified with 8-13Hz fre-

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quency and 30-50 μV in amplitude. These waves are emitted by the parietal and occipital regions of the brain and they exemplify the mental states such as consciousness, quietness or being at rest, thinking and blinking. The β are of the range of 14 - 30 Hz in frequency and 5-20 μV in amplitude.

They are generated by the frontal region of the brain in response to consciousness, alertness and thinking. The θ waves have a frequency range of 4-7 Hz and an amplitude of less than 30 μV. They come from parietal and temporal regions of the brain. The θ waves are generated during emotional pressure, interruptions of consciousness, or deep physical relaxation of the brain. The frequency and amplitude ranges of δ waves are of 0.5-3 Hz and 100-200 μV respectively. They are generated by parietal and temporal regions of the brain and they are connected with deep sleep, unconsciousness and anesthetized conditions. Finally, the γ band is 31-50 Hz in frequency range and 5-10 μV in amplitude.

They are representatives of cognition and perceptual activity. It is evident from the above that same kinds of waves are generated by the different parts of the brain, and a given emotion is generated by a combination of wave bands. For instance, brain waves related to thinking could be a combination of alpha and beta waves. As such, modeling the EEG analysis may not be effectively done by mathematical techniques pertaining to wave analysis. Based on the proven potential of (AI) techniques to model non-algorithmic systems, we have been motivated to use, Artificial Neural Network [18], an approach to AI [19], to model EEG wave analysis to detect associated emotions.

D. Artificial Neural Network

ANN has been the oldest AI technique, which was originated in the early 1940s [6]. It is a model of human brain which encompasses a network of neurons. The neurons in an ANN work as processors while the connections work as memories. This technology can learn from even non-algorithmic, noisy, and incomplete data and model solutions which cannot be algorithmically computed.

Among other features of the brain, ANN is capable of implementing cognitive tasks such as classification, generalization, recognition and abstraction. Typical computer model of single neuron ANN is depicted in Figure 5. In the ANN model, each neuron computes the functions of summation and activation.

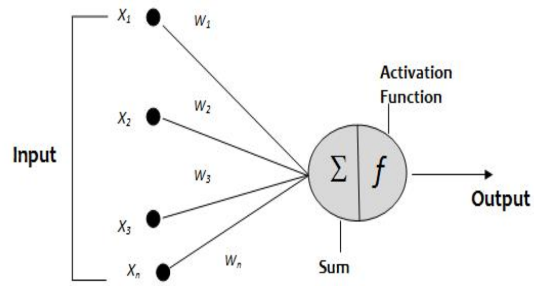

Fig. 5 . ANN with a single neuron

In the ANN model, the inputs x1, x2, x3, ….. xn are bound with the neuron with the corresponding weights: w1, w1, …wn. The weighted sum, net, of the input is considered as the effect on the neuron due to the input. The output generated by the neurons is computed by applying an activation function f on the weighted sum net.

If the f (net) is greater than a certain threshold value T, we say that the neuron is fired due the input applied. If the neuron is fired, then the neuron produces an output value. A typical ANN comprises of multiple layers with many neurons in each layer. An ANN can learn a given data set by adjusting the weight over the learning cycles. Long established research in ANN has shown that any complex real world problem can be modeled by a three-layer artificial neural network with one input layer, one output layer and one middle layer, known as hidden layer. Further it was noted that an ANN provides more generalized solutions, when the number of hidden layers is increased in the ANN architecture.

E. Training of ANN

There are two modes of training of ANN. They are known as supervised training and unsupervised training. The supervised learning is applied to model the real world problems where the training data are available as pairs of inputs and corresponding desired outputs. Many applications such as pattern recognition, object identifications, etc. are developed through supervised training mode.

In contrast, the unsupervised training is applied for the inputs which have not got corresponding output values. This mode of training is suitable for discovery of trends, models, patterns, etc. in a given data set. In both modes of training, there are specific learning algorithms. Among others, back-propagation training algorithm has been the most popular training algorithm for supervised learning

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of multi-layer ANN. Training of ANN for our research in EEG recognition has also been done in the supervised mode with the use of back-propagation training algorithm. The choice of the supervised mode of training is trivial as we train the EEG wave signals knowing whether the particular wave refers to an attentive or a non-attentive session.

F. Mobile Application

Our research is not confined to identification of attentive and non-attentive sessions; it goes a step further to generate a vibration alert to the user to inform him/her of the situation of his/her alertness. For this purpose, we selected mobile telephone technology that comes with wireless communication via Bluetooth. It is undisputed that mobile phone has already become one of the most widely used, powerful and user-friendly technologies in the modern world. In our research, a smart phone with Android operating system has been used to communicate the result of the EEG wave recognition and to generate a vibration alert to the user when the attention is distracted. In this sense, the ANN has been built to run on a smart phone. However, building of an ANN for given scenario requiring attention should be done on a PC with the use of the Framework described below. This is because the Framework is too large to execute on a smart phone for building the ANN. Once the ANN is built on a PC, which runs the Framework, an ordinary smart phone then can run the application.

IV. METHODOLOGY

We have developed a Software Framework for modeling the regaining of attention in real world tasks requiring attention. In the first place, the Framework allows capturing of EEG signals and preprocesses the signals for training an ANN.

The Framework with the trained ANN can be used as a device for analyzing the level of attention of a person when involving a particular task. The Top Level Architecture of the Framework is shown in Figure 6. Next we briefly discuss the role of each module in the architecture.

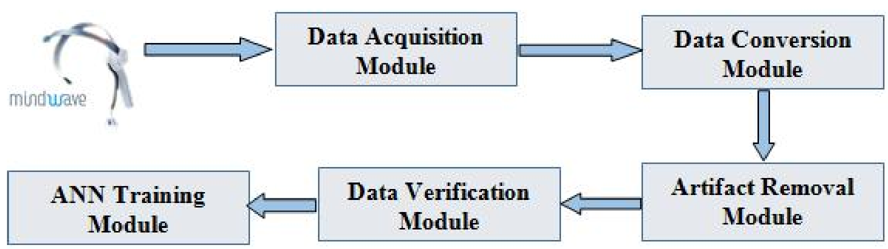

Fig. 6 . Top level architecture of the framework

A. Data Acquisition Module

The Data Acquisition module receives EEG brain wave signals from the NeuroSky Mindwave headset. This headset comes with a single dry sensor, which is specifically designed to receive attention-related EEG waves. The sensor is fitted to capture the brain waves emitting through the left frontal (Fp1) area of forehead. In the Framework, this module can acquire the EEG signals from any attentive session such as driving, shooting, listening, etc. The Neuro Sky Mind wave headset outputs the preprocessed time domain frequency band related data during each second. Raw voltage values are output at a frequency of 512. NeuroSky Mindwave headset has been designed to send preprocessed EEG waves to a computer or a similar device via Bluetooth. The Data Acquisition module can also be customized to receive EEG signals from another headset such as Emotive EPOC.

B. Data Conversion Module

Data conversion module receives the time domain analogue signals from the headset through the Data Acquisition module, and it converts these signals to the frequency domain. In this case, the data conversion module uses the Fast Fourier Transformation (FFT) to produce an optimized conversion of EEG waves from time domain to frequency domain. Some standard libraries used for FFT have been built into the Data Conversion Module in the framework. The output of the data conversion module would be the

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value of α, β, θ,δ and γ corresponding to the EEG wave captured. This module can specify the duration at which the α, β, θ,δ and γ should be sent as the output of the module.

C. Artifact Removal Module

As stated, the EEG signals produced by the headset include a combination of brain activities related to a particular task and some artifacts due to various reasons. For instance, an eye blink could add some artifacts for an EEG wave signal generated regarding a certain brain activity. Obviously, it is required to remove the effect of artifacts before processing the EEG signals.

Some filtering techniques that are available in NeuroSky headset were used for removal of effects of artifacts. In addition, we used the Independent Component Analysis (ICA) to filter the unwanted signals. ICA filtering decomposes the disturbed EEG wave signals into independent components thereby allowing the removal of unwanted parts of the signal.

D. Data Verification Module

Data verification module ensures whether the EEG signals collected from a particular session actually represent attention or something else. For example, if we consider the number of mistakes made in a counting exercise as a measure of attention in the session, we should make sure that the number of mistakes actually represents attention and not something else such as concentration or memory.

As such before developing an ANN for a given EEG wave set, Data verification module uses some standard instruments available for measuring the attentiveness. At present, our framework assumes that the EEG waves generated represent the attention. As such this module is yet to be developed.

E. ANN Training Module

ANN Training module is the core of the system. In fact, the functionalities of the above three modules are already built into NeuroSky Mind Wave set to a great extent. All the steps from data acquisition to data verification can be considered as the preprocessing steps to prepare the EEG wave signals for training an ANN. The module for training of Artificial Neural Network has been supplied with various training algorithms and strategies. Since backpropagation algorithm is popular for training of ANN in supervised mode, the current ANN module mainly implements the said algorithm. This module could be extended with various training algorithms.

F. Android App Mobile Interface

The framework has been designed to train an ANN and install in a smart mobile phone. As such we have also developed an android App to execute the trained ANN from a smart mobile phone. The Android App can also work as the interface for the Framework for building ANN for attentive sessions and application of trained ANN to investigate attention level regarding desired tasks or sessions. More importantly, the App has also been developed to have the ability to monitor and maintain attention and to send a vibration alert so that the user can regain the lost attention without further delay.

V. RESULTS

Framework has been used to build an ANN by considering data generated in a listening test of IELTS examination. Given that listening is a well-known task requiring attention, we have used IELTS listening test results for building an ANN for our experiment. In order to generate data, we applied IELTS listening tests for 40 students. The duration of the listening test was limited to 5 minutes, and a similar test was repeated for 4 times. Repeating the similar test for several times was done to generate more data for training of the ANN to achieve a higher level of generalization. It should also be noted that 5-minute sessions for 4 times were recorded, instead of recording 20-minute durations at once to avoid overhead of processing large EEG wave files by the Framework.

On the other hand, knowing the fact that when the duration is longer the attention is lower, we did not want to generate data from a session where the attention could be knowingly low. During these sessions, the framework collected the EEG wave signals and recorded at a sampling rate of 512.

Further, filtering is applied on EEG data with a cutoff frequency of 50Hz. It should be noted that single subject comprises of EEG waves generated for 5 minutes for 4 such repeat sessions at a rate of one EEG wave per second. Thus, the number of EEG waves considered for one subject turnout was to be 1200, i.e. 4x5x60. Regarding each subject, we applied 1200 EEG wave signals to the ANN. Each of these wave signals generated an attention value between 0

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and 1. Note that the mean value of attention of a single subject over 1200 EEG wave signals was computed as the measure for attention of a given subject. Regarding each subject, the actual attention level was computed as a measure of the scores obtained by the particular student in the IELTS.

Having preprocessed the EEG wave signals through three modules, the Framework trained an ANN according to the three-layer architecture shown in Figure 7. According to Figure 7, five wave bands of the signal, namely, delta, theta, alpha, beta and gamma were used as the components of an input to the ANN. Furthermore, the output layer of the ANN was designed with a single neuron to generate the output between 0 and 1.

The score of IELTS marks for each session was used as a measure for the attention. ANN training was carried out using Backpropagation training algorithm. We used 50% of the data collected to build the ANN and the remaining data for the testing purpose.

Generation of a vibration alert is an essential feature of our project. This feature enables timely notification to the user when the mind starts wandering. The effect of the vibration alert generated by Mobile App was evaluated by interviewing each student. They were unanimous that vibration alert generated by the mobile App enabled them to immediately detect the moment at which the attention was disrupted. This vibration alert brings the mind back quite naturally, like when a sleeping person is awakened by another person sitting next to him/her.

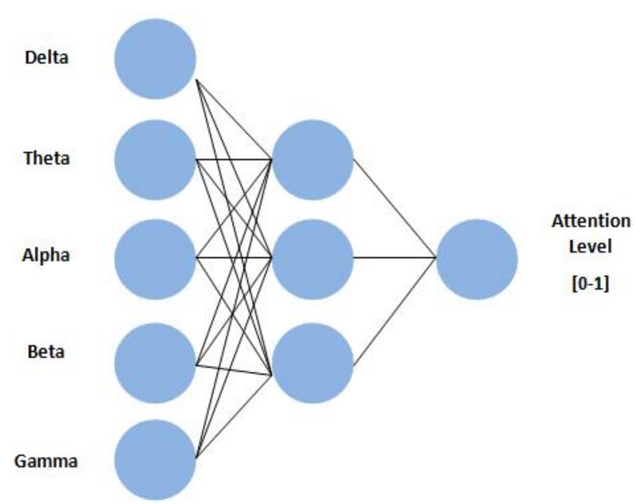

Fig. 7 . Architecture of the artificial neural network

TABLE 1
RESULTS FROM THE EXPERIMENT

Subject	Mean Attention Level	IELTS Test Marks
Subject 1	75	80
Subject 2	77	92
Subject 3	88	100
Subject 4	61	55
Subject 5	42	45
Subject 6	22	40
Subject 7	16	32
Subject 8	91	100
Subject 9	60	82
Subject 10	44	40
Subject 11	55	70
Subject 12	78	90
Subject 13	80	100
Subject 14	61	62
Subject 15	42	25
Subject 16	77	68
Subject 17	92	100
Subject 18	85	100
Subject 19	53	70
Subject 20	17	10

VI. DISCUSSION

Table 1 shows the analysis of results generated by the trained ANN, built by the Framework, regarding the experiment conducted with 20 subjects. The results show that the ANN developed using the Framework has been able to determine the level of attention of the students with 75% accuracy regarding 20 subjects. Table 1 also shows that the attention level determined by the trained ANN and the IELTS scores of the listening test have a positive co-relation. At this point, it would be worth discussing why 25% of prediction made by the ANN has been inaccurate. There can be several reasons for this.

Probably the most apparent reason would be that the number of EEG wave signals used for training the ANN may not be adequate. Further, the training would have been more accurate and generalized, if a larger number of hidden layers had been used for the ANN architecture. On the other hand, accuracy may have been influenced by the noise of the EEG data. In other words, the steps of data acquisition, conversion, artifact removal and verification may not have represented the attention level accurately. As stated, the data verification module is yet to be implemented in the framework. Ideally, we should have used a standard instrument for measuring attention level corresponding to each generated EEG signal. However, according to Table 1, attention levels have a positive correlation with IELTS marks. Thus, the use of IELTS scores as a measure for attention in the training of ANN would not be a problem.

Nevertheless, if the training was conducted for a different session, e.g. driving, we would have to use an instrument [20, 21] for validating the representativeness of EEG data for the attention. It should be noted that any data used for attention modeling must be first verified to make sure that the data actually represent the attention. Although Table 1 shows a significant positive correlation between IELTS marks and attention level, we admit that data verification should have been done to comply with the standard practice of research of this nature. It is evident from the result that the Framework for modeling the regaining of attention is very encouraging.

ANN built by the Framework has been able to determine the level of maintaining attention with 75% accuracy. According to users, deploying the trained ANN as an Android App has become a value addition to the attempt in the project. The result of the interview about regaining attention through vibration alert has been very encouraging. Consequently, this tool can be used as a personal device that helps individuals to monitor and cultivate attention. More importantly, this tool can be used in class room scenarios, driving, shooting, reading and many other tasks requiring attention to capture EEG signals for developing an ANN and subsequently to use the trained ANN for investigating the development in attention.

In summary, we conclude that the current Framework offers a simple and low-cost tool kit for modeling the sessions with attention and also a means for giving alert signals for regaining lost attention. The key implication of this research is that the detection of attention loss in a timely manner has a major impact on assisting a person to regain the lost attention thereby allowing the person to maintain focused attention in a session. More importantly, the accessibility of the solution could be enhanced to reach a very wide spectrum of people worldwide through the already popular mobile smart phone.

Obviously, this solution will be of great significance for students to maintain attention in an educational setup, in particular. Literature provides evidence of research in attention maintenance in various sessions. For instance, Kunar and co-workers have studied the attention destruction by the telephone conversations while driving [22]. This research shows the negative effect on attention when attempting to generate words. Tracking of multiple targets with multi focal attention has also been a topic in attention research [23].

Findings of these researches are quite interesting, in contrast to conventional thinking where attention is a single focus phenomena. Of course, it is evident from scenario such as driving, the attention must be maintained over windscreen, side mirrors and rear mirrors. Nature of the attention over multiple objects has a direct connection with research in mindfulness [7]. A research by Hugdahs and colleagues has studied the cognitive control and attention through neuroimaging data [24]. This work has some connection with our research. However, our research is significantly different from these researches, since we do not just monitor the attention, yet enables regaining of attention in timely manner.

VII. CONCLUSION AND FURTHER WORK

As stated in the discussion the Framework for Modeling the regaining of attention has been able to determine the level of maintaining attention with 75% accuracy. This research can lay foundation for several further works. For instance, one further work of this project would be the improving of performance of the ANN built by the Framework. This includes training of the ANN with more input data for an enhanced architecture, use of more techniques for data conversion and artifact removal, and verification of data for their representation for attention. We also intend to do an exciting further work to study how regaining attention through vibration alerts helps to maintain an individual's attention in sessions with longer duration. Undisputedly, maintenance of attention in longer sessions has been a well-known concern in all spheres [25]. Even though we may be able to maintain attention in shorter durations, it is harder to do so in longer durations.

This is because we (human beings) naturally lose attention in longer sessions due to biological and chemical reactions in the brain. However, we believe that our computer-aided solution will be a positive intervention in this regard. For instance, our further work would be able to identify a person's repeated loss of attention that very moment and direct the person to relax for a while for gaining energy. We argue that before attempting to maintain the focused attention, we should be able to detect the moment at which the mind drifts away. This project can also be extended to integrate NeuroSky Mindwave headset with a

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standard tool kit that supports building and experimenting with ANN. From a computational point of view, such work will be a further extension of the utility of the overall framework for attention modeling.

REFERENCES

[1] H. Shankari and R. T. Selvi, "Guidelines to improve software engineering process using artificial intelligence techniques," *I-Manager's Journal on Software Engineering,* vol. 8, no. 4, pp. 33-40, 2014.

[2] M. Dworschak, "Neurotechnology: Growing a brain in Switzerland," 2007 [Online]. Available: goo.gl/8rFqgF

[3] Sugiyatno, I. Djunaedi and N. A. Mahardiono, "Modelling and simulation of hybrid control system in solar cell-battery-super capacitor," *International Journal of Technology and Engineering Studies,* vol. 1, no. 3, pp. 74-80, 2015. **DOI:** 10.20469/ijtes.40002-3

[4] D. Göhring, D. Latotzky, M. Wang and R. Rojas, "Semi-autonomous car control using brain computer interfaces," *in Intelligent Autonomous Systems 12, Advances in Intelligent Systems and Computing*, S. Lee, H. Cho, K. J. Yoon and J. Lee, Eds. Berlin, DE: Springer, 2013.

[5] A. Nijholt and D. Tan, "Playing with your Brain: Brain computer interfaces and games," *in International Conference on Advances in Computer Entertainment Technology*, New York, NY, 2007.

[6] T. Carlson and J. D. R. Millan, "Brain-controlled wheelchairs: A robotic architecture," *IEEE Robotics and Automation Magazine,* vol. 20, no. 1, pp. 65–73, 2013. **DOI:** 10.1109/MRA.2012.2229936

[7] J. Kabat-Zinn, "Mindfulness-based interventions in context: Past, present, and future," *Clinical Psychology: Science and Practice,* vol. 10, no. 2, pp. 144-156, 2003. **DOI:** 10.1093/clipsy/bpg016

[8] B. Graimann, B. Z. Allison and G. Pfurtschelle, "Brain-computer interfaces: A gentle introduction," *in Brain-Computer Interfaces*, B. Graimann, B. Z. Allison and G. Pfurtschelle, Eds. Berlin, Germany: Springer, 2013.

[9] S. Lee, Y. Shin, S. Woo, K. Kim and H. N. Lee, "Review of wireless brain computer interface systems," *in Brain-Computer Interface Systems—Recent Progress and Future Prospects*, R. Fazel-Rezai, Eds. Rijeka, Croatia: InTech, 2013.

[10] C. K. A. Lim and W. C. Chia, "Analysis of single-electrode EEG rhythms using MATLAB to elicit correlation with cognitive stress," *International Journal of Computer Theory and Engineering,* vol. 7, no. 2, pp. 149-155, 2015. **DOI:** 10.7763/IJCTE.2015.V7.947

[11] E. A. Larsen, " Classification of EEG signals in a brain-computer interface system," M.S. thesis, Norwegian University of science and Technology, Trondheim, Norway, 2013.

[12] M. Mustafa, M. N. Taib, Z. H. Murat, N. Sulaiman and S. A. M. Aris, "The analysis of EEG spectrogram image for brainwave balancing application using ANN," *in the UkSim 13th International Conference on Computer Modelling and Simulation, and Art Exhibition*, Cambridge, UK, 2011. **DOI:** 10.1109/UKSIM.2011.22

[13] Wikipedia, "Comparison of consumer brain computer interfaces," 2016 [Online]. Available: goo.gl/Ui2Ne6

[14] S. Wang, J. Gwizdka and W. A. Chaovalitwongse, "Using wireless EEG signals to assess memory workload in the $ n $-back task," *IEEE Transactions on Human-Machine Systems,* vol. 46, no. 3, pp. 424-435, 2016. **DOI:** 10.1109/THMS.2015.2476818

[15] Neuro Sky, "PPR726 Investigating the neuro sky mind ave EEG Headset," 2014 [Online]. Available: goo.gl/WWKe3r

[16] M. Teplan, "Fundamentals of EEG measurement," *Measurement Science Review,* vol. 2, no. 2, pp. 1-11, 2002.

[17] J. D. Bronzino, *The Biomedical Engeneering Handbook*. Florida, FL: CRC Press, 1995.

[18] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Networks,* vol. 61, no. 1, pp. 85-117, 2015. **DOI:** 10.1016/j.neunet.2014.09.003

[19] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*. Upper Saddle River, NJ: Prentice Hall, 2009.

[20] R. A. Baer, "Measuring mindfulness," *Contemporary Buddhism,* vol. 12, no. 1, pp. 241-261, 2011. **DOI:** 10.1080/14639947.2011.564842

[21] N. Md Nor, S. H. Salleh and A. Zubaidi, "Understanding teacher stress when teaching the developed technology by using electroencephalogram (EEG) signals," *Journal of Applied and Physical Sciences,* vol. 2, no. 3, pp. 65-76, 2016.

ISSN: 2414-3103
DOI: 10.20474/japs-3.2.1

DOI: 10.20474/japs-2.3.1

[22] M. A. Kunar, R. Carter, M. Cohen and T. S. Horowitz, "Telephone conversation impairs sustained visual attention via a central bottleneck," *Psychonomic Bulletin and Review,* vol. 15, no. 6, pp. 1135-1140, 2008. **DOI:** 10.3758/PBR.15.6.1135

[23] P. Cavanagh and G. A. Alvarez, "Tracking multiple targets with multifocal attention," *Trends in Cognitive Sciences,* vol. 9, no. 7, pp. 349-354. 2005.
DOI: 10.1016/j.tics.2005.05.009

[24] K. Hugdahl, R. Westerhausen....and H. hämäläinen, "Attention and cognitive control: Unfolding the dichotic listening story," *Scandinavian Journal of Psychology,* vol. 50, no. 1, pp. 11-22, 2009.
DOI: 10.1111/j.1467-9450.2008.00676.x

[25] A. A. Chojaczyk, A. P. Teixeira, L. C. Neves, J. B. Cardoso and C. G. Soares, "Review and application of artificial neural networks models in reliability anal ysis of steel structures," *Structural Safety,* vol. 52, no. 2, pp. 78-89, 2015.
DOI: 10.1016/j.strusafe.2014.09.002

— This article does not have any appendix. —