Survey on Role of Artificial Intelligence in Predicting Mental Alertness for Physically Active Persons using EEG

Keerthika.N [1], E. Sathish [2]

[1, 2] School of Electronics & Engineering, Vellore Institute of Technology, Chennai, India.

Email: [1] keerthika.n2021a@vitstudent.ac.in, [2] sathish.e@vit.ac.in

Abstract

The human brain comprises a complex network of neurons, which supports cognitive actions, body balance, and performing innumerable actions. Electroencephalography (EEG) is a method of recording the electrical activities of the brain, which can be used for several applications, such as prediction of alertness, drowsiness, attention-seeking, motor imaginary movements, emotion, and diagnose the effects of drugs. Advanced Artificial Intelligence (AAI) methods such as Machine Learning (ML) and Deep Learning algorithms (DL) play a vital role in the classification EEG signals. This study presents a systematic review of the prominent research articles which comprehend the identification of mental alertness and the impact of sports in mental alertness. This significant survey infers that, physical activities will intensify the concentration level. The feature extraction, feature selection and classification algorithms in specific to mental alertness were reported and compared. From the cluster of features like relative power, absolute power, power spectral density, spectral power signal entropy, the predominant features viz. relative power and power spectral density were selected using filter, wrapper, LASSO based algorithms with p values of 0.075 and 0.06 respectively. Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), Decision Tree (DT), and Logistic Regression (LR) techniques were used to classify the mental alertness. SVM and ANN were the widely used accurate classifiers for mental alertness, with an accuracy of 87.6% and 96.6%, respectively.

Index Terms— Classification, Feature Extraction, Mental alertness, Sports, Machine learning algorithm.

1. Introduction

The brain has a massive complicated network of neurons, which will support the enormous motor actions in the body. Moreover, the brain is categorized into various lobe regions (refer figure-1), responsible for regulating various activities of the body. EEG is the most essential tool for analyzing brain activities, The raw signals are extracted from the brain with help of EEG electrodes using a 10-20 lead system. The electrode placement is identified with the help of different montages. The EEG frequency ranges are categorized as alpha (8 to 13 HZ), beta (12 to 30 HZ), theta (4 to 8 HZ), delta (0.5to 4HZ), and gamma (30 to 140 HZ). Using the frequency ranges, the dominant working frequency of the human brain can be predicted the stages of mental alertness. [6], [38].

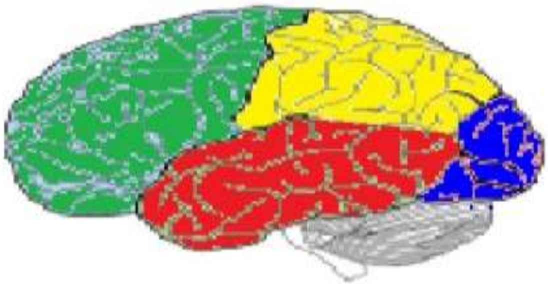

Fig 1. Human brain with lobe regions, Frontal lobe- Green color, Parietal lobe Yellow color, Temporal lobe – Red Colour Occipital lobe – Voilet color 6], [38]

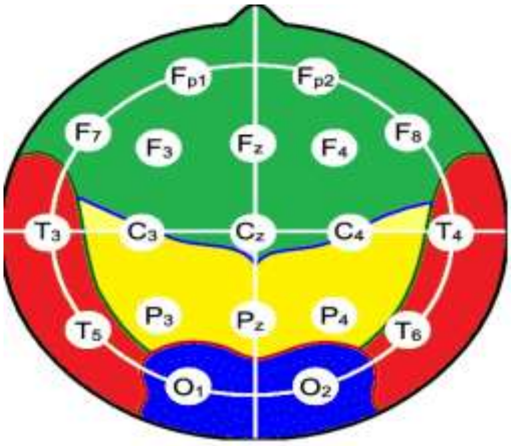

Fig: 2. Electrodes placements of EEG set up in 10-20 lead system [6] & [33] Frontal lobe- Green, Parietal lobe – Yellow, Temporal lobe – Red, Occipital lobe – Violet.

2. Impacts of Physical Activities and Sports on Health

Sport is an essential factor for physical fitness thathelps to maintain the stability of the human mind and body. Various studies clearly state that physical activities or sports activities can improve the cognitive actions of the human brain. A slight improvement in concentration levels was predicted for the people involved in physical activities or sports[19]. A comparison of mental alertness levels of sports and non-sports students was performed by conducting a cognitive test and it was inferred that the alertness level was high for sports students. [34]. Improvement in life span was found in people involved in sports or physical activities [8]. The periodical involvement in sports or physical activities can improve mental alertness and give individuals more social responsibility [20][35] . Periodically doing sports or fitness can reduce the cardiometabolic risk of adults [21].A small significant difference in terms of mental alertness between sports and non-sports students with respect to cognitive performances. The result showed that the body mass index (BMI) was maintained properly and also improve the cognitive actions of individuals involved in sports or physical activities periodically [22] It was inferred from the study that, during a pandemic situation sports persons were unable to involve in sports activities periodically and significant changes in the mental stability. The author observed that, in order to regain their mental alertness, they must involve themselves in the concerned sports activities (like basketball, volleyball, badminton, football, cricket, etc.) [23]. An analysis was made on the professional sports players performing the training sessions periodically in their respective sports. The result proved that there was an improvement in the mental stability and cognitive actions of the individuals were increased self-relaxation time like audio and visual attention etc. [24]

Carried out an approach for physically active adults, whose age was >50 years for improving their cognitive skills in their life. In this study, various fitness tests and cognition tests, namely Aerobic exercise, Plyometric exercise, Resistance training Strength training, Muscle stretching exercises, Physical conditioning, human Walking,Taiji(taichi),Yoga, cognitive tasks, memory-based games, Memory based games, dementia, and executive skills for the given situation for 333 subjects. From this study, it was observed that the individuals involved in sports and fitness can improve their cognitive skills and it was suggested to the adults to do atleast 45 to 50 minutes of fitness or any other physical activities or sports [32]. The relationship between physical activity and cognitive performances in adolescents and young adults was examined. According to the results of this poll cognitive abilities were maintained in old age for adults involved in aerobics and resistance training [46].

From the above survey, it is inferred that, doing any sports or physical activities help to increase the concentration and ability to maintain a healthy body throughout our lives.

Table 1. Physiological and Psychological Effects on Health of Performing the Physical Activities or Sports

The green color indicates the strong contribution of that activity, the orange color indicates the moderate contribution to that activity, and the red color indicates the weekly contribution to that activity.

Reference	Physiological and Psychological Effects on Health	Fitness	Aerobic Exercise	Athletes	Team Sports	Cognitive Enhancements
18	Physical activities and sports can help to reduce the disease occurring in the body and improve cognitive actions [18]	🟢	🟢	🔴	🔴	🟢
19	Significant changes were predicted in the concentration level while doing sports and physical activities.[19]	🟢	🟢	🟠	🟠	🟢
20	The individuals involved in sports or physical activities can increase their mental alertness and social responsibility.[20]	🟢	🟠	🟢	🟢	🟢
21 & 30	Periodically doing sports or fitness can reduce the cardiometabolic risk of adults [21], [30]	🟢	🟢	🟢	🟢	🔴
22	The students involved in sports or physical activities can maintain their Body Mass Index (BMI) and cognitive performances [22].	🟢	🟢	🟢	🟢	🟠

23	Involvement in training and participation in events (like district, state, national, and international level events) can improve the mental stability of the athletes.[23]	🟢	🟡	🟢	🟡	🟢
24	Increasing the self-relaxation time after their training period can improve the sports performance of the players in the events or tournaments.[24]	🟢	🔴	🟢	🔴	🟢
25	The individuals performing the fitness or aerobic exercises periodically can be free from the depression state and improve their Hippocampal state,[25]	🟢	🟢	🔴	🔴	🟢
26	Significant impacts on cognitive actions and mental alertness can be seen for the persons involved in physical activities and cognitive games. [26]	🟢	🟢	🟢	🟢	🟢
27	Periodically participating in fitness and sports can reduce the anxiety level of adults [27].	🟢	🟢	🟢	🟢	🟢
28	Individuals involved in 12 weeks of power training can improve their mobility. [28]	🟢	🟡	🟢	🟢	🔴
29	Periodically increase physical activities or sports can improve the neuropsychological functions of the body [29]	🟢	🟢	🟢	🟢	🟢
31	Sports and physical activities can free individuals from diseases and mental stress.[31]	🟢	🟢	🟢	🟢	🔴

3. Classification and Feature Extraction Methodologies for Eeg Signals

EEG is the best tool for acquiring signals from the brain. An extensive survey was carried out an analyze the important features and classification algorithms in aiding the efficient outcome.

Feature extraction plays a vital role in EEG signal analysis. In this study, the features such as relative power, absolute power, power spectral density, spectral power signal entropy, and Shannon entropy will be extracted from the preprocessed EEG signals. After feature extraction, the features were selected with the help of feature selection algorithms. All the

algorithms were performed with their own metric system. Filter-based methods were performed by Pearson correlation and
Chi-square test, Wrapper-based algorithm by the Recursive feature elimination method and Embedded based algorithm by the LASSO method. All the feature selection techniques were used to select the relevant features and remove the irrelevant and redundant features from the dataset. This method helped to improve the accurate classification of data. The classification algorithms were simulated with the help of ANVOA and MATLAB. The result showed that the alpha relative power and lower beta relative power were increased and remaining all the features were decreased [7][2]. A study was performed in the education environment to classify the mental alertness of the students. The linear features such as relative power, absolute power, peak variance, skewness, and kurtosis were extracted for concentration analysis of students. The author observed that for the concentration level the power spectral density feature was predominantly used and the classification was performed with ANN with an accuracy of 81.02% [8].

The author analyzed the linear features (absolute power, kurtosis, peak variance, relative power, and Hjorth) and non-linear features (Kolmogorov complexity entropy, Shannon entropy, power-spectrum entropy, correlation) and various parameter classifications for identifying the depression state and compared with the normal person. The classifiers were used as, SVM, KNN, ANN, and CT. The result showed that the significant accuracy of the classification is 79.27% using KNN.[9] The analysis was carried out on the classification of sleepiness and identified the deficits of alertness from sleepiness for the adults. The Psychomotor Vigilance Task (PVT) was performed for the classification of circadian misalignment and the percentage of pre-closure of the eyelid was calculated in the class environment. The results proved that the accuracy of the pre-closure eyelid is 75.51% [1]

The analysis was performed to predict and classify the alertness and drowsiness state of students in the classroom environment. The response time feature was extracted and it can be classified with the statistical tool ANOVA. The results proved that an increase in delta, theta, and alpha bands while performing the vigilance task [10][12].

The study classified the mental alertness and drowsiness of the adults in the classroom environment. The linear features such as spectral power signal entropy and response time were extracted. The various classifiers such as SVM, ANN, DT, LR, and KNN were trained and the classifier having maximum accuracy was chosen to classify the alertness state of the adults. The result showed that the accuracy of 81.42% and 87.27% was obtained using SVM and ANN [13].

From the literature, various classification and feature selection algorithms were trained for analyzing the mental alertness of sports and non-sports students. Table 1.1 summarizes the physiological and psychological effects of periodical involvement in sports or physical activities. Table 1.2 discussed the comparison of various approaches in classifiers and feature extraction based on EEG signals for mental alertness. From these tables, it is observed that the predominant features viz. relative power and power spectral density with p values of 0.075 and 0.06 respectively. The various classifiers used for the classification were SVM, ANN, KNN, DT, and LR. The predominant classifiers were used for mental alertness SVM and ANN with of 87.6% and 96.6%, accuracy respectively.

Table 2. Comparison on Various Approaches in Classification Methods and Feature Extraction from the Eeg Signal

Data Set	Feature Extracted	Methodology	Classification of accuracy	Test values
Real-Time (Swedish students) [41]	Mean, Standard Deviation (SD) Variance. [41]	ANOVA and SPSS [41]	——	By doing Physical activities people are healthy and their life span also increased. P= 0.06 (low-0.50 & high - 0.29-1.11) [41]
Real-Time (600 elite Estonian athletes- Men & Women) [44]	Average, SD [44]	t-tests, and Chi2 tests [44]	——	Depression- P=0.032, Anxiety-P=<0.001, Faitgue-0.01, Insomnia-P=0.01 [44]
Real-Time (Athletes) [45]	Average, SD [45]	Kraepelin test and ANVOA [45]	——	beta-1 power for trained participants' value of alpha is p= 0.075 and beta-1 is 0.030 [45]
Real-Time (university students) [13]	Response time [13]	SVM with RBF kernel and ANN [13]	SVM with RBF kernel and ANNs with F1-score of 85% and 88% Control Condition- 84% & 87.27% [13]	——
Real-Time data (offline mode for drivers) [37]	The Relative Power of responsible frequency [37]	ANN and ANVOA. [37]	ANN with F score is 95% confidence interval and also the beta relative power is increase significantly in the process. [37]	——
Real-Time (30 healthy subjects) [38]	Alertness, Drowsiness, and Sleepiness.[38]	DWT and MLPNN [38]	The classification rate was 93.3% alertness, 96.6% drowsiness, and 90% sleepiness. [38]	——
Data- 19 features [40]	Time analysis, wavelet decomposition, spectral analysis [40]	ANN and lambda of Wilks criterion.[40]	classification of accuracy using ANN - Drowsiness- 87.4% & Alertness state- 83.6% [40]	——
Real-time data set (Normal &	Linear features Non-linear	MATLAB (version	The results prove that the KNN is the best	——

depression state person). [9]	features. [9]	R2014a) - for cross-validation process, SVM, KNN, CT, and ANN. [9]	for classification and the accuracy is 79.27%. [9]	
Real-time data set (17 health people) age (23 to27). [10]	Response time of Alpha, Beta, Delta, Theta, and Gamma. [10]	ANVOA test, BCI system. [10]	The result proves that tonic power was increased in the delta, theta, and alpha bands while increasing the visual attention task [10]	----
Real-time data set [11]	Response Time, Power Spectral Density () [11]	ANN and ANOVA test. [11]	Perform evaluation metrics and the classification of accuracy is 83.95% [11]	----
Real-Time data. [12]	Covert Visual Spatial Attention (CVSA) [12]	t-test. [12]	After the CVSA task, the goalkeeper alpha frequency was slightly increased and the accuracy is around 73.70% [12]	----
Real-time data (students). [13]	Spectral Power, Signal Entropy, and Response time. [13]	SVM, ANN, DT, LR and KNN. [13]	The performance metrics were calculated. The results show that SVM and ANN give better accuracy. (AB condition-78.62% & 81.42%, Control Condition- 84% & 87.27%.) [13]	----
Real-time data set (30 people). [15]	Alertness, Drowsiness, and Sleepiness. [15]	DWT and MLPNN. [15]	The accuracy of classification is 93.3% alertness, 96.6% drowsiness, and 90% sleepiness. [15]	----
Beth Israel Hospital	(ECPD), (MA), Power	WT and ANN [16]	The distribution probability of ECPD	----

database (18 members) age of 32 and 56 years. [16]	Spectrum Density (PSD). [16]		is 90.72 % [16]	
Real-time data set (drivers). [17]	Spectral Analysis (Alertness, Drowsiness). [17]	ANN and Lambda of Wilks Criterion [17]	Classified the 5 datasets with ANN. The result shows that the accuracy of classification is 87.4% drowsy state and 83.6% Alertness state [17]	——

4. Conclusion

This survey aimed to clarify facts and figures for interested learners and researchers to learn about the role of AI in feature extraction, selection, and classification of EEG signals for various stages of mental alertness. It also helped in emphasizing the role of physical activities and sports in improving mental alertness. The impact of classifiers such as KNN, SVM, ANN, LR, and DT on EEG signals obtained from the public domain and real-time data sets was discussed. With the data sets, the maximum classification of accuracy was accomplished by using SVM and ANN for mental alertness. This study also highlights the significant contributions, implementation, and limitations for the classification of mental alertness for persons with periodic participation in physical activity.

References

[1] Corsi-Cabrera M, Sánchez AI, del-Río-Portilla Y, Villanueva Y, Pérez-Garci E. Effect of 38 h of total sleep deprivation on the waking EEG in women: sex differences. *Int J Psychophysiol*.2003;50(3):213-224.

[2] R. R. Johnson, D. P. Popovic, R. E. Olmstead, M. Stikic,D. J. Levendowski, and C. Berka, ‘‘Drowsiness/alertness algorithm development and validation using synchronized EEG and cognitive performance to individualize a generalized model,’’ *Biol. Psychol.*, vol. 87, no. 2, pp. 241–250, May 2011

[3] I. Belakhdar, W. Kaaniche, R. Djmel, and B. Ouni, ‘‘A comparison between ANN and SVM classifier for drowsiness detection based on single EEG channel,’’ *in Proc. 2nd Int. Conf. Adv. Technol.* Signal Image Process. (ATSIP), Mar. 2016, pp. 443–446

[4] Hsu, Chih-Wei et al. “A Practical Guide to Support Vector Classication.” (2008).

[5] H. Shabani, M. Mikaili, and S. M. R. Noori, ‘‘Assessment of recurrence quantification analysis (RQA) of EEG for development of a novel drowsi- ness detection system,’’ *Biomed. Eng. Lett.*, vol. 6, pp. 196–204, 2016.

[6] J.Satheesh Kumar and P. Bhuvaneshwari “Analysis of Electroencephalography (EEG) Signals and Its Categorization–A Study” in *Elsevier -Procedia Engineering*., vol 38, pp.2525-2536, 2012.

[7] Hillard, Brent et al. “Neurofeedback training aimed to improve focused attention and alertness in children with ADHD: a study of the relative power of EEG rhythms using

custom-made software application." *Clinical EEG and neuroscience* vol. 44,3 (2013): 193-202.

[8] Ismail, Lina Elsherif, and Waldemar Karwowski. "Applications of EEG indices for the quantification of human cognitive performance: A systematic review and bibliometric analysis." *PloS one* vol. 15,12 e0242857. 4 Dec. 2020,

[9] Hanshu Cai,1 Jiashuo Han,1 Yunfei Chen,1 Xiaocong Sha,1 Ziyang Wang,1 Bin Hu,1,2,3 Jing Yang,4 Lei Feng,5 Zhijie Ding,6 Yiqiang Chen,7 and Jürg Gutknecht8, " A Pervasive Approach to EEG-Based Depression Detection", *Hindawi,* volume 2018 | Article ID 5238028 2018 .

[10] Ko, Li-Wei et al. "Flexible graphene/GO electrode for gel- free EEG." *Journal of neural engineering* vol. 18,4 10.1088/1741-2552/abf609. 18 May. 2021

[11] Roberto Sanchez-ReolidFrancisco Lopez de la RosaMaría T. LopezAntonio Fernandez-Caballero, "One-dimensional convolutional neural networks for low/high arousal classification from electrodermal activity"*Bio Medical Signal processing and control.*volume 71 Jan 2022.

[12] Jeunet, Camille et al. "Uncovering EEG Correlates of Covert Attention in Soccer Goalkeepers: Towards Innovative Sport Training Procedures." *Scientific reports* vol. 10,1 1705. 3 Feb. 2020

[13] Contreras-Jordán, Onofre R., et al. "Physical Exercise Effects on University Students' Attention: An EEG Analysis Approach." *Electronics*, vol. 11, no. 5, p. 770., Mar. 2022,

[14] Md. Asadur Rahman, Md. Mamun or Rashid, Farzana Khanam, Mohammad Khurshed Alam and Mohiuddin Ahmad, "EEG based Brain Alertness Monitoring by Statistical and Artificial Neural Network Approach" *International Journal of Advanced Computer Science and Applications(ijacsa)*, 10(1), 2019.

[15] Subasi, A., Kiymik, M.K., Akin, M. *et al.* Automatic recognition of vigilance state by using a wavelet-based artificial neural network. *Neural Comput & Applic* **14**, 45–55 (2005)

[16] Naiyana Boonnak, Suwatchai Kamonsantiroj, and Luepol Pipanmaekaporn" Wavelet Transform Enhancement for Drowsiness Classification in EEG Records Using Energy Distrribution and Neural Network." *IJMLC Vol. 5(4)*: 288-293 I, 2015

[17] Abidi, A., Ben Khalifa, K., Ben Cheikh, R. et al. Automatic Detection of Drowsiness in EEG Records Based on Machine Learning Approaches. *Neural Process Lett*, May (2022).

[18] Malm, Christer et al. "Physical Activity and Sports-Real Health Benefits: A Review with Insight into the Public Health of Sweden." *Sports (Basel, Switzerland)* vol. 7,5 127. 23 May. 2019

[19] Barbosa, Ana et al. "Physical Activity and Academic Achievement: An Umbrella Review." *International journal of environmental research and public health* vol. 17,16 5972. 17 Aug. 2020.

[20] Eime, R.M., Young, J.A., Harvey, J.T. et al. A systematic review of the psychological and social benefits of participation in sport for children and adolescents: informing

development of a conceptual model of health through sport. *Int J Behav Nutr PhysAct* 10, 98(2013).

[21] White DA, Willis EA, Ptomey LT, Gorczyca AM, Donnelly JE. Weekly Frequency of Meeting the Physical Activity Guidelines and Cardiometabolic Health in Children and Adolescents. *Med Sci Sports Exerc*.2022Jan1;54(1):106-11

[22] Jarnig G, Kerbl R, van Poppel MNM. Change in BMI and Fitness among Primary School Children in Austria: A 24-Month Follow-Up Study of 303 Children Measured before and during the Ongoing COVID-19 Pandemic. *Sports (Basel).* 19;10(5):78. May 2022.

[23] Tamm AL, Parm Ü, Aluoja A, Tomingas T. Changes in the Mental Health Indicators and Training Opportunities for Estonian Elite Athletes Compared to the COVID-19 Isolation Period. *Sports* 11;10(5):76. *(Basel*). May,2022

[24] Mikicin M, Orzechowski G, Jurewicz K, Paluch K, Kowalczyk M, Wróbel A. Brain-training for physical performance: a study of EEG-neurofeedback and alpha relaxation training in athletes. *Acta Neurobiol Exp* (Wars). 2015

[25] Kandola Aaron, Hendrikse Joshua, Lucassen Paul J., Yücel Murat,"Aerobic Exercise as a Tool to Improve Hippocampal Plasticity and Function in Humans: Practical Implications for Mental Health Treatment", *Frontiers in Human Neuroscience* ,volume 10, 2016.

[26] Smith GE. Healthy cognitive aging and dementia prevention. *Am Psychol*. 71(4):268-75 June,2016.

[27] Stubbs B, Vancampfort D, Rosenbaum S, Firth J, Cosco T, Veronese N, Salum GA, Schuch FB. An examination of the anxiolytic effects of exercise for people with anxiety and stress-related disorders: A meta-analysis. *Psychiatry Res*,.May 2017.

[28] Hvid LG, Strotmeyer ES, Skjødt M, Magnussen LV, Andersen M, Caserotti P. Voluntary muscle activation improves with power training and is associated with changes in gait speed in mobility-limited older adults - A randomized controlled trial. *Exp Gerontol*. PMID: 27090485,Jul,2016..

[29] Jackson WM, Davis N, Sands SA, Whittington RA, Sun LS. Physical Activity and Cognitive Development: A Meta-Analysis. *Journal of Neurosurg Anesthesiol,* Oct;28(4):373-380, 2016.

[30] Gjevestad, Gyrd O et al. "Effects of Exercise on Gene Expression of Inflammatory Markers in Human Peripheral Blood Cells: A Systematic Review." *Current cardiovascular risk reports* vol. 9,7 (2015)

[31] Thomas RJ, Kenfield SA, Jimenez A. Exercise-induced biochemical changes and their potential influence on cancer: a scientific review. *Br J Sports Med*. 2017

[32] Northey JM, Cherbuin N, Pumpa KL, Smee DJ, Rattray B. Exercise interventions for cognitive function in adults older than 50: a systematic review with meta-analysis. *Br J Sports Med*. 2018 Feb;52(3):154-160.

[33] Alotaiby, T., El-Samie, F.E.A., Alshebeili, S.A. et al. A review of channel selection algorithms for EEG signal processing. *EURASIP J. Advance Signal Process.* 2015.

[34] Etnier JL, Nowell PM, Landers DM, Sibley BA. A meta-regression to examine the relationship between aerobic fitness and cognitive performance. *Brain Res Rev*.Aug 30;52(1):119-30, 2006.

[35] Etnier, Jennifer L et al. "A meta-regression to examine the relationship between aerobic fitness and cognitive performance." *Brain research reviews* vol. 52,1 (2006).

[36] Md. Asadur Rahman, Md. Mamun or Rashid, Farzana Khanam, Mohammad Khurshed Alam and Mohiuddin Ahmad, "EEG based Brain Alertness Monitoring by Statistical and Artificial Neural Network Approach" *International Journal of Advanced Computer Science and Applications(ijacsa)*, 10(1), 2019.

[37] Subasi, A., Kiymik, M.K., Akin, M. *et al.* Automatic recognition of vigilance state by using a wavelet-based artificial neural network. *Neural Comput & Applic* **14**, 45–55(2005).

[38] Naiyana Boonnak, Suwatchai Kamonsantiroj, and Luepol Pipanmaekaporn, "Wavelet Transform Enhancement for Drowsiness Classification in EEG Records Using Energy Coefficient Distribution and Neural Network," *International Journal of Machine Learning and Computing* vol. 5, no. 4, pp. 288-293, 2015.

[39] Agustina Garcés Correa, Lorena Orosco, Eric Laciar,Automatic detection of drowsiness in EEG records based on multimodal analysis, *Medical Engineering & Physics*,Volume36,Issue,2,2014.,

[40] Malm, C., Jakobsson, J., & Isaksson, A. (2019). Physical Activity and Sports-Real Health Benefits: A Review with Insight into the Public Health of Sweden. *Sports (Basel, Switzerland)*, *7*(5), 127.

[41] White, David A et al. "Weekly Frequency of Meeting the Physical Activity Guidelines and Cardiometabolic Health in Children and Adolescents." *Medicine and science in sports and exercise* vol. 54,1 (2022)

[42] Tamm, Anna-Liisa et al. "Changes in the Mental Health Indicators and Training Opportunities for Estonian Elite Athletes Compared to the COVID-19 Isolation Period." *Sports (Basel, Switzerland)* vol. 10,5 76. 11 May. 2022

[43] Mikicin, Mirosław et al. "Brain-training for physical performance: a study of EEG-neurofeedback and alpha relaxation training in athletes." *Acta neurobiologiae experimentalis* vol. 75,4 (2015)

[44] Voss, Michelle W et al. "Exercise, brain, and cognition across the life span." *Journal of applied physiology (Bethesda, Md. : 1985)* vol. 111,5 (2011).