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Detection and Classification of Human Stress Analysis using EEG Signals

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ABSTRACT

In day to day lifestress plays significant role in the quality of human life. Emotion plays a major role in motivation, perception, cognition, creativity,attention, learning and decision-making.In recent years, stress analysis by using electro-encephalography (EEG) signalshas emerged as an importantareaof research. EEG signalsare one of the most important means of indirectly measuring the state of the brain. EEG (Electroencephalogram) signal is a neuro-signal which is produced due the different electrical exercises in the mind. These signals canbe captured and processed to get the necessary data which can be used to detect some psychological changes in early stage. In this proposed system, EEG signal dataset is pre-processed and components with ocular effect are extracted from the EEG signal. Classification of stress level is accomplished by applying SVM (Support-Vector Machine) algorithm which gives the better accuracy.

Keywords : Stress analysis, EEG signals, ocular effect, feature extraction, classification, SVM

I. INTRODUCTION

Stress is a body's method for reacting to a challenge. Human stress can have an impact on aperson's mental and physical well - being. Stress can lead to a change in behavior and in physiology. Many people suffer from stress in everyday life. Stress is related to human work in one way or other. Stress originates from different sources such as time pressure while working in company, responsibility, economic problem or physical factors such as noise. Signs of stress of a human being are tension, anxiety, anger, frustration or irritation by things over which he has no control.

According to the World Health Origination (WHO), stress is the major problem of human being and it has large effect on physical as well as mental health. Stress detection is an on-going research topic among both psychologists and engineers. Wearable sensors and bio signal processing technologies are developed for detecting the human stress. There are various bio signal processing technologies use for human stress detection such as Electroencephalography (EEG), Electrocardiography (ECG), Electromyography (EMG), Blood Pressure (BP), Blood Volume Pulses (BVP), Galvanic Skin Resistance (GSR), Respiration and Skin Temperature (ST) etc.A few methodologies utilize the temperature of the finger [15], human signals [16] and eye squint [17] as a methodology to identify stress. Late methods utilize warm imaging [18], physiological signals [19,20] for stress recognition. Identification of stress is a standout among the best research topic point for psychologists as well as engineers also.There are three kinds of stress:

Acute Stress: This stress is for short time span in which some energy present and bring thrill. for example roller coaster ride.

Episodic Stress: This stress is for longer span of time in which individuals makes self-harm or having absurd demands or stressing.

Chronic Stress: This stress is for long haul, which results in unfortunate and hazardous for human well being.

EEG signal gets captured by EEG MindWave Neurosky headset and these signal get separated according to the recurrence ranges, to be specific delta(1-4 HZ), theta(4-8 Hz),alpha(8-13 Hz), beta (13-20 Hz) and gamma (generally >20Hz).Voltage fluctional of the scalp is somewhere in the range of 20 and 100uV[15].These EEG signals are captured utilizing various electrodes normally accessible in clinics. These electrodes are place on the scalp, utilizing 10:20 technique to catch flag. Primary aim of this undertaking is to build up a convenient and ease ongoing framework for gathering as well as analyzing of the signal for the discovery of stress level of human.

The traditional stress recognition framework is based on physiological signs and outward appearance techniques. The real disadvantage is the vulnerability that ascents because of various outer variables like sweating, room temperature, anxiety. Some strategies like hormone investigation have a downside of obtrusive procedure. There is requirement for a strategy that is non-intrusive, precise, accurate and reliable. This research work expects to identify stress dependent on EEG as EEG shows a decent connection with stress.

II. LITERATURE SURVEY

Studies involving the stress analysis using EEG signals and implementing the techniques can be found in literature. Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT), Discrete Cosign Transform (DCT) and so on can be utilized for highlight extraction previously ordering the information. Sulaiman et al. [16] proposed a mix of EEG Asymmetry and Spectral Centroids strategies to distinguish one of a kind example of human pressure. Ghostly Centroids procedure was broadly utilized in discourse and sound acknowledgment as a result of its strength to perceive the prevailing recurrence [17-19]. Poulus et al. [20] utilized EEG phantom power and mean recurrence of Alpha band as a component to NN (Neural Network) so as to recognize individual's trademark. Additionally, kNN classifier was utilized to identify and group human identity and attributesfrom the EEG flag design when tuning in to music [21-24].

III. PROPOSED SYSTEM

In this proposed system, EEG signal dataset is pre-processed using Notch filter. ICA (Independent component analysis) is applied to pick the component with ocular effect. And then Hilbert Transform is applied for feature extraction. Classification of stress level is done by implementing SVM (Support-Vector Machine) algorithm which will provide the better accuracy.

A.EEG Signals

Electroencephalography is a medicinal imaging strategy that peruses scalp electrical action produced by cerebrum structures. The electroencephalogram (EEG) is characterized as electrical movement of a substituting type recorded from the scalp surface in the wake of being grabbed by metal terminals and conductive media.EEG signal comprises of various mind waves reflecting cerebrum electrical action as indicated by terminal positions and working in the neighboring cerebrum areas.Along these lines electroencephalographic perusing is a totally non-obtrusive strategy that can be connected more than once to patients, typical grown-ups, and kids with for all intents and purposes no hazard or restriction A remote EEG gadget, which is a head set was set by universal 10-20 framework.The terminals were appended to the scalp at position AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 as appeared in Figure1.

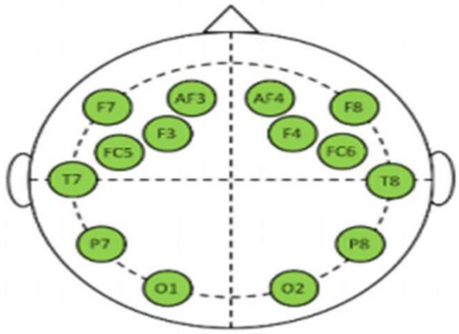
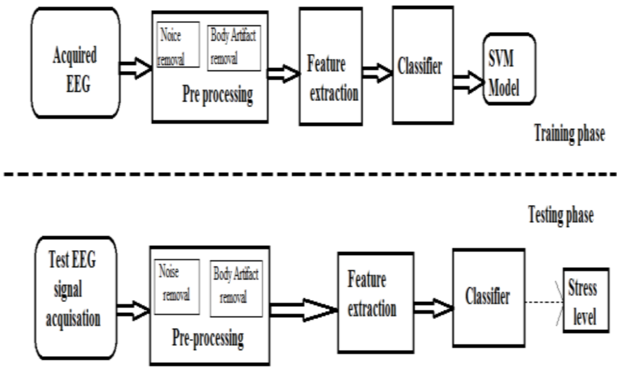


Figure 1. Electrode placement on the scalp.

One of the essential commotion (ancient rarities), that is Ocular relic expulsion is disposed in the process. The EEG rhythms lie in the recurrence scope of 0.3 Hz to 44 Hz. The visual relic happens at 0.1-16 Hz.



B. EEG Pre-Processing

Raw EEG is contaminated with noise from different form and sources. As EEG has very small amplitude, filtering out unwanted noise is a critical step to extract useful information. Ocular artefacts that arise due to body movement areeliminated.The notch is a very selective filter with a very high rejection just for a tiny frequency band around the selected frequency. It will not attenuate other frequencies, which belong to the EEG signal.Notch filter is utilized to dismiss the 60 Hz or 50 Hz electrical cable amplitude.

C. ICA to pick the Component with Ocular

Artifact: Independent Component Analysis is an amazing asset for wiping out a few significant kinds of non-cerebrum relics from EEG information. Eye advancements cause changes to the electric fields around the eyes, and accordingly over the scalp. As a result, EEG chronicles are normally basically misshaped, and their understanding hazardous. Different procedures have been proposed to beat this issue, stretching out from the rejection of data contrasting temporarily with huge eye advancements, to the departure of the assessed effect of visual development from the EEG. Independent Component Analysis is a powerful tool for eliminating several important types of non-brain artefacts from EEG data and allows the user to reject many such artifacts in anefficient and user-friendly manner.

D.Feature Extraction and Classification

A versatile component extraction method Hilbert Transform was connected to separate pertinent highlights in time-recurrence area. It is the important way to deal with uncovers data covered up in the sign considering the non-stationary nature of the signal.The purpose of this stage is to map EEG into theconsequent stress state. An adaptive featureextraction technique Hilbert Transform wasapplied to extract relevant features in time frequency domain. It is the relevant approach tounearth information hidden in the signalconsidering the non-stationary nature of the signal.

The element vector got through Hilbert transform is arranged into impartial or three dimensions of pressure (stress-low, stress-medium and stress-high).Support Vector Machine (SVM) is used to classify the stress levels.

SVM: The objectives of SVM are isolating the information with hyper plane and stretch out this to non-direct limits utilizing bit trap.For computing the SVM, the objective is to effectively arrange every one of the information.

If Yi= +1;wxi +b>=1

If Yi= - 1; wxi + b $\leqslant$ 1

For all I; yi (wi + b) $\geqslant$ 1

In this condition x is a vector point and w is weight and is likewise a vector. So to isolate the information ought to dependably be more noteworthy than zero. Among all conceivable hyper planes, SVM chooses the one where the separation of hyper plane is as huge as could be expected under the circumstances.

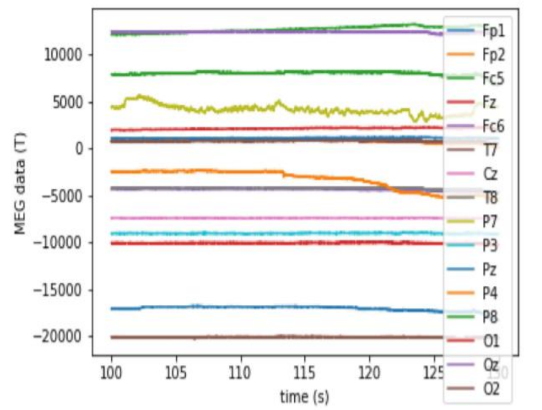
IV. RESULTS

The proposed system is implemented using Python.Dataset is imported. The stress analysis of a person usually depends on various factors ranging from their age, gender to their fatigue level, its really important to consider all these factors as they play a very important role in calculating the stress level of a person.

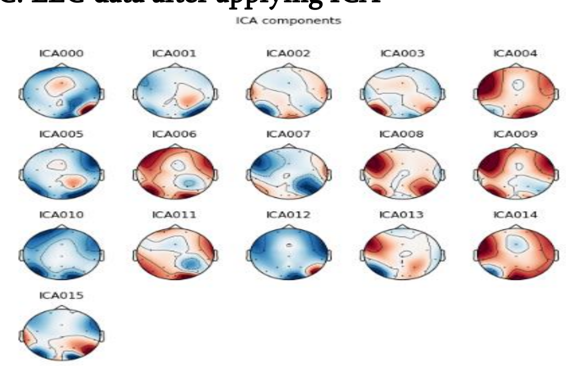
A. Importing EEG Data set:

	0	-16640	1075.3	7197.5	1501.7	-4080.5	872.67	-7446.6	-3852.2	1030.8	-8910.8	959.38	-2181.5	8054.1	-10051	13269	-1
0	0.001953	-16635	1079.3	7204.3	1506.2	-4079.5	877.05	-7445.6	-3850.3	1030.4	-8908.5	960.23	-2170.2	8059.6	-10066.0	13262	-1
1	0.003906	-16637	1078.2	7205.8	1505.0	-4078.3	884.08	-7446.9	-3848.2	1034.6	-8907.6	960.58	-2172.2	8063.1	-10064.0	13268	-1
2	0.005859	-16640	1075.8	7200.0	1505.7	-4082.1	883.72	-7445.1	-3846.9	1029.3	-8909.2	961.27	-2172.0	8065.8	-10062.0	13270	-1
3	0.007812	-16641	1077.9	7203.8	1510.0	-4076.7	880.42	-7439.3	-3840.8	1039.5	-8897.2	970.28	-2159.3	8071.2	-10049.0	13282	-1
4	0.009766	-16642	1077.4	7200.6	1511.4	-4078.4	878.31	-7436.7	-3848.6	1032.8	-8896.2	970.89	-2162.7	8070.9	-10044.0	13285	-1

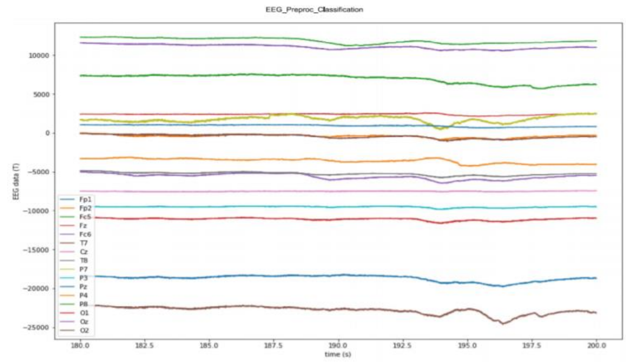
B. Extracted EEG data of different electrodes



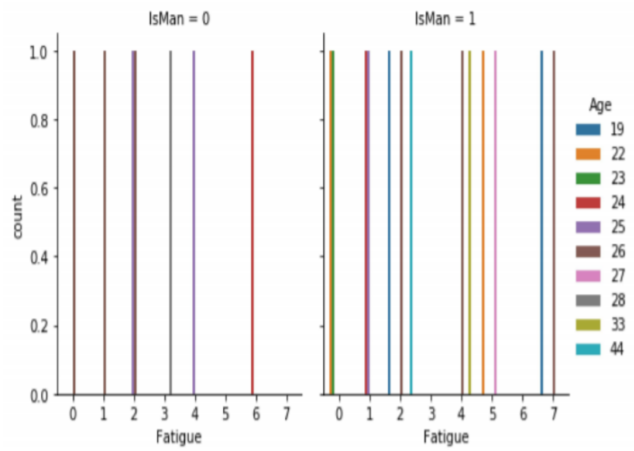
C. EEG data after applying ICA



D. EEG signal after pre-processing



E. Final output



V. CONCLUSION

EEG signals gives betterfeature extraction results for stress classification compared to other signals. Theproposed framework improves accuracy of feature extraction and classification technique.

Further, the proposed framework will be helpful in such a way that it may lead to a new mode of medication to relieve a person's/ subjects stress level after appropriately interpreting EEG signals.So, this proposed system is an EEG-based stress analysiswhich captures the constant EEG signals and structures the complete loop by showing various qualities according to the electrical signals on the scalp. The useful information from the EEG signals and implemented SVM as classifier and obtained accuracy of 83.34%. The outcomes reported the feasibility of using EEG for stress analysis, which is significant for clinical intervention and avoidance of physical and psychological wellbeing issues.

VI. REFERENCES

[1] Hu, B., Peng, H., Zhao, Q., Hu, B., Majoe, D., Zheng, F. and Moore, P. Signal Quality Assessment Model for Wearable EEG Sensor on Prediction of Mental Stress. IEEE Transactions on Nanobioscience 14 (5) (2015).

[2] Ursin H, Eriksen HR. The cognitive activation theory of stress. Psycho neuro endocrinol 2004; 30: 567-592.

[3] Garret JB. Gender differences in college related stress. Undergr J psychol 2001;14: 5-9.

[4] Kalas, M.S. and Momin, B.F. Stress Detection and Reduction using EEG Signals. International Conference on Electrical, Electronics, and Optimization Techniques 12 (2016) 59-62.

[5] Dunkel SC, Lobel M. Stress among students. N Dir Student Serv 1990.

[6] Abouserie R. Sources and levels of stress in relation to locus of control and self-esteem in university students. Edu psychol 1994; 14: 323-330.

[7] Hunt J, Eisenberg D. Mental health problems and helpseeking behaviour among college students. J Adol H 2010; 46: 3-10.

[8] Lahane, P., Vaidya, A., Umale, C., Shirude, S. and Raut, A. Real Time System to Detect Human Stress Using EEG Signals. International Journal of Innovative Research in Computer and Communication Engineering 4 (4) (2016).

[9] Begum S, Ahmed MU, Funk P, Xiong N, Scheele BV. Using calibration and fuzzification of cases for improved diagnosis and treatment of stress. Proc European workshop 2006; 113-122.

[10] Healey JA, Picard RW. Detecting stress during real-world driving tasks using physiological sensors. IEEE Trans Intel Transp Sys 2005; 6: 156-166.

[11] Haak M, Bos S, Panic S, Rothkrantz LJ. Detecting stress using eye blinks and brain activity from EEG signals. Proc Interact Interf 2009: 35-60

[12] Pavlidis I, Dowdall J, Sun N, Puri C, Fei J, Garbey M. Interacting with human physiology. Comp Vis Imag Unders 2007; 108: 150-170.

[13] Poh MZ, McDuff DJ, Picard RW. Non-contact, automated cardiac pulse measurements using video imaging and blind source separation. Optics Express 2010; 18: 10762-10774.

[14] Fei J, Pavlidis I. Thermistor at a distance: unobtrusive measurement of breathing. IEEE Trans Biomed Eng 2010; 57: 988-998.

[15] Kulkarni, S.P., Potale, S.B. and Bairagi, V.K. Brain Monitoring for Healthy Living. IEEE ICCSP, 2015.

[16] N. Sulaiman, M. N. Taib, S. A. Mohd Aris, N. H. Abdul Hamid, S. Lias and Z. H. Murat, "Stress features identification from EEG signals using EEG Asymmetry & Spectral Centroids Techniques," in Proceedings of the IEEE EMBS on Biomedical Engineering and Science (IECBES), 2010, pp. 417-421. K. K. Paliwal, "Spectral Subband Centroids Features for Speech Recognition," in Proceedings of the International Conference on Acoustics, Speech and Signal Processing (ICASSP), 1998, pp. 617- 620.

[17] J. S. Seo, M. Jin, S. Lee, D. Jang, S. Lee and C. D. Yoo, "Audio Fingerprinting Based on Normalized Spectral Subband Centroids," in Proceedings of the International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2005, pp. 213-216.

[18] M. L. Massar, M. Fickus, E. Bryan, D. T. Petkie and A. J. Terzuoli Jr., "Fast Computation of Spectral Centroids," Journal of Advanced Computing Mathematics, vol. 35, no. 1, pp. 83-97, June 2010

[19] M. Poulos, M. Rangoussi, N. Alexandris and A. Evangelou, "On the use of EEG features towards person identification via neural networks," in Proceedings of the International Conference on Acoustic, Speech and Signal Processing (ICASSP), 1999, pp. 1-35.

[20] S.Ito, Y. Mitsukura, K. Sato, S. Fujisawa and M. Fukumi, "Study on Relationship between Personality and Individual Characteristic of EEG for Personalized BCI," in Proceedings of the IEEE International Conference on Computational Technology in Electrical and Electronics Engineering (SIBIRCON), 2010, pp. 106-111.

[21] T. Lan, A. Adami, D. Erdogmus and M. Pavel, "Estimating Cognitive State using EEG signals," Journal of Machine Learning, vol. 4, pp. 1261-1269, 2003.

[22] R. Khosrowabadi, C.Q. Hiok, Abdul Wahab and K.A. Kai, "EEGbased emotion recognition using self-organizing map for boundary detection," in Proceedings of the International Conference on Pattern Recognition, 2010, pp. 4242-4245.

[23] S. Ito, Y. Mitsukura and M. Fukumi, "A Basic Method for Classifying Human Based on an EEG Analysis," in Proceedings of the International Conference on Control, Automation, Robotics and Vision (ICARCV), 2008, pp. 1783-1786.