Early Stress Detection and Analysis using EEG signals in Machine Learning Framework

Jharna Agrawal¹, Manish Gupta², and Hitendra Garg³

¹,²,³GLA University, Mathura

jharna.agrawal_phd.ec20@gla.ac.in, manish.gupta@gla.ac.in, hitendra.garg@gla.ac.in

Abstract. Stress, a psychological phenomenon that represents the body's natural defense against predators and danger, has emerged as the biggest social problem of the 21st century especially during the Covid-19 pandemic. Various techniques or methods such as PET, ECG, EMG, MRI exist to detect and quantify stress. Physiological features produced throughout the brain's electrical activity are documented by a medical technique known as an electroencephalogram (EEG).

In this context, this paper posits a comparative analysis of the above-described methods of stress detection and accentuates on stress detection methodology using EEG signals, as EEG is a perfect non-invasive tool, widely used in clinical and research domains. The fractal dimension (FD) method, which is an indicator of curve irregularities, has been used in the detection of stress for feature extraction, applying three FD algorithms viz. Higuchi, Katz and Permutation Entropy. For classification, this study aims to apply and compare a number of classic machine learning algorithms based on accuracy, precision and sensitivity. This paper also presents a novel architecture, based on EEG analysis in MATLAB, fractal dimension used for feature extraction along with Machine Learning processes for classification i.e., Random Forest and Artificial Neural Network which is useful for early-stage stress detection, analyzing different stress levels viz. mild, moderate and high accuracy and providing ways for people to cope with stress in order to enhance their performance.

1. Introduction

According to the World health organization nowadays stress has become a common feeling faced by people due to the COVID-19 outbreak caused by coronavirus disease. Several external factors bereavement, quarantine, isolation, loss of income, job issues and few internal factors like rapid thinking, lack of flexibility, unrealistic expectations lead to stress and have shown to have an inimical effect on performance[1]. Meanwhile, as a result of neurological and mental complications, such as delirium, hysteria, and stroke, COVID-19 itself may lead to the uncertainty surrounding the coronavirus which is the hardest and toughest thing to deal with. Undoubtedly, this leads to a catastrophically pandemic situation.

Stress is stated as a condition of immense pressure or mental strain in layman’s language, whereas in research studies it is described as a mechanism of the body to respond to a challenge [2] or reaction of the body to mental, emotional, or physical pain [3]. This mechanism is known as the fight-or-flight mechanism. It also affects partially or entirely the practicality of everyday work and the nation’s economy too[4].

Stress can trigger mental and behavioral changes because there is no relaxation between different challenges [5]. Stress symptoms are depicted by these changes. Precisely, physical symptoms include sweating, cramps, fainting, headache, high blood pressure, muscular aches and sleeping
difficulties whereas emotional symptoms count anger, anxiety, depression, forgetfulness, moodiness and loneliness.

These symptoms may further change the behavior of stressed patients unexpectedly, such as food craving, sudden angry outbursts, higher tobacco or alcohol consumption, and frequent crying are observed as significant stress symptoms [6]. Not only do stressful conditions cause dysfunctional behavior, but they can also exacerbate hypertension, cardiovascular disease, bowel disease, if the stress continues [4],[6] for a long duration.

So, it is of prime concern for the researchers to detect stress at its early stage and at the same time before it triggers any significant health complications, people must be aware of the effects of being over-stressed. Stress impacts overall human wellbeing and weakens the immune system. Therefore, research community is focusing to find out the best way for detecting stress at an early stage to prevent stress becoming persistent and proposing strategies to stop causing irreversible damages. Public and Private sector, Medical, Education, Research, Defence, Space, Sports and Social life require low cost, accurate and effective technology for stress detection and reduction techniques to abet society.

1.1 Methods of Stress Detection

It is evident that stress is ubiquitous and thus it has been considered as a social problem of the 21st century. The human cerebrum is considered the primary wellspring of stress by researchers [5]. Two kinds of responses i.e. physiologically and physically measured stress as shown in tables I and II [7].

| S.No | Technology Name               | Physical Measures     |
|------|-------------------------------|-----------------------|
| 1.   | Automated Gesture Analysis    | Body Gesture          |
| 2.   | Infrared Eye Tracking         | Eye Activity          |

Both facial expression and Physiological indicators methods are the foundation of the conventional stress detection system. Due to less number of facial expressions, emotion dissembling and individuals with alexithymia, there may be difficulties and constraints in physical measures. The biggest pitfall with physical technologies to measure stress is the ambiguity that exists due to different external factors such as anxiety room-temperature, sweating [8],[27]. These external factors are detected by observing the continuous brain waves produced by the human brain.

| S.No | Technology Name               | Symbol     | Physiological Measures              |
|------|-------------------------------|------------|-------------------------------------|
| 1.   | Electrocardiography           | ECG        | Heart’s electrical activity         |
| 2.   | Electroencephalography        | EEG        | Electrical activity in the brain    |
| 3.   | Electrodermal Activity        | EDA        | Skin Response                       |
| 4.   | Galvanic Skin Response        | GSR        |                                     |

Research studies show that human physiological characteristics derived from physiological signals are used to assess the intensity of stress. There is a clear distinction between male and female responses to stress as it is considered as a subject-specific event. Hence features which are physiological in nature occurring the brain in the form of electrical activity, forms the foundation of stress detection methods [9].
Various methods have been developed to assess and study the stress level, either on the basis of a questionnaire, surveys or monitoring of people which quantify the changes in physiological signals. In online real-time applications, physiological signals can be measured and analyzed with higher accuracy for the quantification of stress [3], which can be divided into two categories:

i) Invasive type

ii) Non-invasive type.

Invasive type method has two techniques, in general:

- Local Field Potential (LFP)
- Electrocorticography (ECoG)

These two methods are known to contribute high resolution and high precision in the temporal and spatial axes. But there is minimal coverage for such methods. Research study shows that ECoG is a method where electrode pads are attached directly to the brain surface for obtaining brain waves. Therefore, It has got merit that high resolution and wide bandwidth are achieved, though comes with a limitation of brain surgery required for electrode placement [3],[5].

There is a downside to invasive procedures in some techniques, such as hormone analysis [8] which arises the need for a noninvasive, effective, accurate, and reliable methods. Stress which can be detected from human physiological signals includes the following techniques in another category i.e., Noninvasive methods [5],[7],[10],[11]. Table 3 shows a comparison of these methods:

| S. No. | Noninvasive Methods | Advantage | Limitations |
|-------|---------------------|-----------|-------------|
| 1.    | Positron Emission Tomography(PET)- slightly Invasive imaging procedure | High spatial resolution | Bounded temporal resolution, high expense, significant safety restriction due to radiotracers. |
| 2.    | Functional Magnetic Resonance Imaging (fMRI) | Moderately good or high spatial resolution | Temporal response of the blood supply is very low. |
| 3.    | Magnetic Encephalography(MEG) | High resolution | Very expensive |
| 4.    | Electrocardiography (ECG) | Equipment widely accessible, Accuracy verified in different populations | Sensitivity poorer in comparison to other stress imaging techniques, poor Specificity |
| 5.    | Electromyography (EMG) | Most suitable, reliable, viable and accurate instrument for measuring muscle activities, | Reduced clinical yield in few cases, other technical limitations emerge with obesity and advanced age, Complexity issues in signal interpretation |
| 6.    | Blood Pressure (BP) | Ease to use, reproducibility of values, sensitivity of measurement, availability of normotensive data. | The lack of prospective mortality data, so cannot be used to decide whether treatment is indicated. |
| 7.    | Blood Volume Pulses (BVP) | Unobtrusiveness and low costs. | Need of individual calibration and drift in it over short intervals. |
| 8.    | Galvanic Skin Resistance (GSR) | Immediate availability and low cost | Diurnal Fluctuations cause time of assessment to influence results. |
| 9.    | Electroencephalography (EEG) | Outstanding temporal resolution, low cost, no real safety limitations. | Low spatial resolution and elevated noise. |
For quicker, affordable and accessible insights about brain functions with a tight temporal resolution, EEG is the best choice over ECG, EMG, PET, fMRI and other above-mentioned methods with some significant results [2], [3], [5], [7], [9], [11], [14]. It can be inferred that EEG is a great instrument since it depends on the method which is not invasive receives feedback from stress hormones, so it can act as an accurate and reliable tool for stress calculation [2], [3], [7], [8], [9] for cognitive and neuroscience research [14].

1.2 Electroencephalogram (EEG)

The human brain is the first and foremost entity to respond to different feelings or emotions [11]. The brain, serving as the control processing unit of living beings controls the human body through direct or indirect electrical signals. The spontaneous electrical activity of the brain, produced due to the presence of neurons is noted by a medical method known as an electroencephalogram (EEG) [15]. An EEG signal is generated due to the electric currents flowing among the brain cells in the cerebral cortex region of the brain. Small metal discs associated with thin wires which are known as electrodes are placed on the scalp and then signals are sent to a device to record the data. Because these electrical changes are quick, fine time resolution on the order of a millisecond or even microsecond is achieved [7], [9]. EEG recordings are depicted as graphs of electrical energy generated by the brain versus time.

An EEG channel is established by considering the potential difference, measured across two electrodes which are placed at a distance, and then summed potential of neurons is recorded. Generally, EEG is measured using 10-20 Standard electrode system [15], as shown in Fig. 1.

Nowadays EEG is a useful method to monitor the nonlinear electrical function of the brain’s nerve cells and used in recent studies as a valuable electrophysiological tool for early-stage detection, evaluation and treatment.

2. Literature Review

The following comprehensive overview elucidates the entire endeavors taken so far worldwide in the field of stress detection and reduction techniques. The accumulation and exploration of data which is generally, physiological in nature and the recognition of the correlation between perceived stress and numerous physiological characteristics were the subjects of previous work on stress measurement, which follows as:
Richa Gupta et al. [5], emphasized the integration of 5 algorithms using EEG signals to increase the accuracy of mental stress identification. The Whale Optimization Algorithm was modified in the paper, to choose the optimal kernel in the SVM classifier as a stress detection technique, while a coherent set of algorithms (NLM, DCT, and MBPSO) has been applied for pre-processing and extracting features along with selection. Further, the EEG signals accumulated from 14 patients have been tested to detect the extent of stress. Using precision, sensitivity, specificity, and F1 scores with values of 96.36 percent, 96.84 percent, 90.8 percent and 97.96 percent, the proposed method was validated and it has proven better than the existing ones. Psychiatrists and health consultants may find this algorithm useful for diagnosing the stress level.

Sami Elzeiny et al. [7], all kinds of stress are considered to be dangerous, but this paper actually shows that temporary stress is beneficial if the body comes back to its original state. It makes the body conscious of injuries and equipped to respond to chaotic circumstances. Here, the stress phenomenon and need for early detection of stress are emphasized. This paper reviews stress discovery methods and strategies for management.

Prashant Lahane et al. [13], detected emotion using the standard DEAP dataset by executing a new feature extraction technique named as Teager-Kaiser Energy Operator, which is based on Electroencephalography (EEG). This work compares the executed TKEO feature extraction method with Relative Energy Ratio, and Kernel Density Estimation methods regarding accuracy and exhibited that TKEO enhances feature extraction as compared to other conventional techniques. The experimental results stated that TKEO, when applied with classification algorithms i.e. Neural Network, Classification Tree, and K-Nearest Neighbor, provided relatively higher accuracy than KDE and RER for channel 1 alpha band and channel 17 beta band for stress identification.

Jindal K. et al. [15], study compared various techniques of machine learning for stress assessment dependent on the responses which are physiological, in regulated environs. Electrocardiogram (ECG), galvanic skin response (GSR), temperature, and respiration were documented during a stress evaluation conducted in the laboratory. Further, using a general approach, six machine learning techniques were examined. The effects display that Bayesian networks and support vector machines provide better classification results which are 84.6 percent and 82.7 percent respectively.

Ranjith C. et al. [16], accentuated that feature selection and classification processes should be considered for stress related factors. By selecting more accurate characteristics, feature extraction will enhance the classification efficiency of EEG signal prediction. One of the human stress prediction methodologies implemented to work accurately by adapting the action of Finite Variance Scaling (FVS) is the Fuzzy K-Nearest Neighbor (FKNN) classifier. The most popular procedure, Discrete Wavelet Transform (DWT), is used in a well-defined way to perform the feature extraction process. By combining it with the EEG Asymmetry method, this can be further optimized by identifying a particular pattern of human stress that can contribute to accurate feature selection results. No earlier research process, where the variance of the beta band would imply the disparity in mental workload, has taken over these ideas. It concludes that music provided positive results to reduce stress.

Qianli Xu et al. [17], introduced suggest a novel technique known as Cluster-Based Study to estimate stress considering physiological signals. This research paper categorizes the subjects into subgroups, to utilize the inherent homogeneity of the stress responses collected from subjects within the cluster. This automatically accommodates the intersubject discrepancies and emphasizes that the comprehensive accuracy of stress assessment is increased.

Chee-Kong Alfred Lim et al. [18], determined degree of a single electrode of NeuroSky, MindWave EEG headset can distinguish brainwave in terms of stressor extent. The MATLAB environment for processing EEG signals is developed in this research. Cheaper EEG headsets can
be used for diagnosing different mental illnesses by minimizing the number of electrodes required.

**Tong Chen et. al. [26]**, introduces a system for non-contact psychological stress identification using a human physiological response. In this research, for detecting human stress, a Hyper Spectral Imaging (HSI) camera is used to acquire data regarding tissue oxygen saturation (StO2).

### 3. Comparison of different Classifiers

This study aims to perform a comparative analysis of existing different classifier algorithms in order to find optimal detection solution and proposing a novel approach for stress reduction.

**Table 4- Classifier Research Paper List with accuracy**

| S. No. | Research/References | Participants | Classifier | Accuracy (%) |
|--------|---------------------|--------------|------------|--------------|
| 1.     | Sanay et. al. [20]  | 28           | NB         | 71.43        |
| 2.     | Lin et. al. [21]    | 6            | KNN and NBC| 71.77        |
| 3.     | Lahane et. al.[13]  | 16           | KNN        | 83.33        |
| 4.     | Saeed et. al. [22]  | 33           | SVM        | 85.20        |
| 5.     | Saidatul et. al. [24]| 5           | NN         | 91.17        |
| 6.     | Khosrowabadi et. al [23]| 26          | KNN and SVM| 90.00        |
| 7.     | Ranjith et.al. [16] | 05           | FFNN with PSO | 93.25    |
| 8.     | Subhani et. al. [27] | 42          | LR, SVM and NB | 94.60    |
| 9.     | Al Shargie et. al. [26] | 18       | SVM and ECoC | 95.37    |
| 10.    | Jun et. al. [25]    | 10           | SVM        | 96.00        |
| 11     | Gupta et. al. [5]   | 14           | SVM        | 96.36        |

From the table it can be concluded that classic machine learning algorithms such as Support Vector Machine (SVM), Naive Bayes (NB), K-Nearest Neighbour (KNN) achieved an accuracy of between 70 and 90 percent and Domas et. al. [9], rendered F1 score ranged from 70 percent to 86 percent. The classification strategies did not outperform each other significantly. But the experimental results proved that Vijean et. al. [24], acquired 91.17 percent precision using the Neural Network algorithm. In contrast to the current algorithms for stress detection and classification with the EEG signal, Ranjith et. al. [16], the application of FFNN-PSO achieved greater performance in terms of accuracy of 93.25 percent, sensitivity of 92.14 percent, and specificity of 97.52 percent where as other classifiers like LDA (Linear Discriminant Analysis), SVM (Support Vector Machine) and RVM (Relevance Vector Machine) acquired accuracy from 89 percent to 90 percent, sensitivity from 88 percent to 90 percent and specificity from 95 percent to 96.9 percent. This emphasized on better performance of neural networks Machine Learning algorithms over classic Machine Learning algorithms.

### 4. Proposed Methodology

In order to achieve EEG signals, electrodes are placed on the scalp following Standard Electrode 10–20 system. The accumulation of raw EEG signals is always temporal and has low Signal to Noise Ratio and low spatial resolution in their preliminary configuration. Hence, it is arduous to identify them using any mechanism.

In most of the methods, for the demonstration of a signal, Fourier Transform is carried out for processing EEG database. EEG spectrum covers distinctive waveforms that effectively fall
within five frequency bands, known as alpha, beta, gamma, delta and theta. Such methods have been used widely and proved beneficial for various EEG characterizations, but Fast Fourier transform (FFT) is highly sensitive to noise.

On the other side, Power spectrum estimation as a parametric way such as autoregressive (AR) minimizes the spectral loss problems and provides improved frequency resolution, but along with a limitation that is not reversible in nature and more sensitive to numerical round-off errors. It is evident that the EEG signals are non-stationary; therefore parametric methods are not suitable for frequency decomposition of EEG signals.

Hence, for such transient signals, representation and analysis in time-frequency domain is recommended [7],[29]. The benefit of frequency-related parameters is that they are less vulnerable to fluctuations in signal quality, because of electrode placement or the physical characteristics of subjects considered [29].

To find the major occurrence band components of EEG signals, concept of a multi-scale filter with different sizes of filter window is proposed. It is evident that the cortically generated EEG is frequently contaminated by several non-cerebral artifact origins viz. eye blinks, ocular movements along with electrical disturbances and instrumentation noise. Therefore EEG signal pre-processing is the most essential aspect before fetching information or extracting features from EEGs. To achieve this ocular artifact removal technique is implemented [28]. After pre-processing of EEG data down sampling is required to decreases cost and time of processing.

The extraction of synthetic and informative features from EEG signals [17],[30] is based on Fractal Analysis, a new scientific paradigm that has been successfully applied in many domains, including medical and physical sciences [30].

A fractal can be contemplated as an entity made up of various self-similar objects and has a property that exposes a finer structure of an object when magnified.

Strict self-similarity and statistical self-similarity are two kinds of fractal dimension. Artificially created mathematical objects possess the property of strict self-similarity, whereas statistical self-similarity is exhibited by natural objects. When the fragments of an object are identical to the whole, on average then statistical self-similarity is identified [31].

Fractal Dimensions (FD) are therefore measurements of the self-similarity and self-iterative property of the signals. To detect and categorize specific states of physiological function, the non-linear feature fractal dimension has been proposed.

The fractal dimension measures the complexity of the EEG signal. In the proposed methodology, the non-linear feature, Fractal Dimension has been considered. Based on that, three algorithms of Fractal Dimension i.e., Higuchi, Katz, and Permutation Entropy [17],[30] have been recommended for early detection of stress and measurement of different stress levels. The obtained data from the subjects are being used to train the classifiers.

Thus the extracted characteristics of reported EEG behavior will be given as input to the classifier. The data classification indicates the stressed or relaxed mode of the subject. In this proposed methodology, two classifier algorithms viz. Artificial Neural Network [18],[26] and Random Forest are considered for classification and training purposes.
over multiple other algorithms. Further, inventions are proposed as a stress management strategy to reduce stress and improve performance.

5. Proposed System Architecture

Based on the methodology, the proposed system architecture is useful to explore the different stress levels viz. mild, moderate and high stress effectively and provide methods for reducing stress among people in order to enhance their efficiency.

6. Conclusion

It is evident that nowadays stress has evolved as the most significant factor to measure people's wellness, euphoria, and contentment. It can be concluded from this work that recognition of emotions or stress using EEG technique, has the ability to alter the way of detection and treatment of some severe health problems over other existing techniques, as it gives us a more diverse view on states of stress that might not be possible for one to express. Concluding, the incorporation of signal-processing techniques such as Fast Fourier Transform or Discrete Wavelet Transform is proposed along with the statistical features acquired by the time-frequency analysis of EEG signals to improve accuracy.

This study proposes that classification algorithms which use fractal dimension for feature extraction typically provide better results than others. It is important to note that classifier results are based on both the classifier and the features to be applied into that classifier to turn that classification into a success. Artificial neural networks (ANN) and deep neural networks (DNN) which are recommended for implementing Machine Learning classifier algorithms tend to outperform classic machine learning algorithms in real applications, as they achieve greater accuracy.

Finally, the paper has depicted novel system architecture for monitoring health and wellness, assessment of treatment efficacy through early detection of physiological disorders using EEG method describing its merits over other existing methods for stress detection.
The implementation of proposed architecture requires further practical validation which would require the collection of subjective datasets on a wide scale, subject to future research. Besides, the future work will also consist of better analytical detection algorithms and further refinement of objective evaluation would require more focused work to fully leverage the potential benefits of machine learning in EEG processing.

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