Brainwave Biofeedback for Stress Detection

*Agrim Sharma 1, Kalaipriyan,T..1**

1 School of Computer Science and Engineering, Vellore Institute of Technology, Chennai Campus, Tamilnadu, India.

Corresponding author: Kalaipriyan.t@vit.ac.in*

ABSTRACT

In the fast paced high volume world we live in today, many are under greater stress than ever before. The potential use of Brainwave Biofeedback as a novel and non-invasive stress monitoring and reduction tool is examined. This process is based on observing and responding to one's own brain activity in real-time for gaining self-insights and controlling them. Recent research has also demonstrated that people who practice this regularly produce lower levels of stress. It is able to do so as it helps people relax thus increase emotional resilience. Users gain instant feedback relating to their current brainwave pattern that allows them to condition and manipulate mental states, thus feeling more in control of their stress reactions. The following research unpicks the neuroscience,26-33 demonstrating the potential for Brainwave biofeedback to enhance both emotional health and cognitive functions. As the need for simple, personalized stress reduction solutions is gain further focus, this study will be featured as an exciting advancement in helping people to take a proactive approach by finding ways to challenge stress which in turn helps to resolve their mental health problems. It also supports further investigation and development of the practical use for stress alleviation and brain health.

KEYWORDS

Machine Learning, Pattern Recognition, Neuroscience, Health and Wellness

1 Introduction

The pressures of contemporary life have led to an unprecedented surge of stress-induced complaints in the relentless pursuit of technological advancement and social improvement. As they navigate the thicket of an accelerating connected world, the demand for innovative and personalized strategies of recharging and unwinding are becoming more pressing. To meet this need, in the present article we introduce a new approach to stress reduction that integrates Brainwave Biofeedback (a technology that quasi-instantaneously measures and displays cortical activity) with contemporary.

SVM, Naive Bayes and CNN Analyses (B) machine learning methods including Support Vector Machines (SVM), Naive Bayes or Convolutional Neural Networks (CNN). Stress, a ubiquitous and intricate problem is the destroyer of sound mental and physical health, cutting across all boundaries. Conventional stress management methods often lack the most individual and targeted manner how to counteract the variety of personal reaction on situations with demanding quality. To address this bottleneck, the proposed approach aims to exploit the capacity of Brainwave Biofeedback -- which enables instantaneous monitoring and feedback on a person's brainwave activity. This approach aims to deliver personalised and just-in-the-moment interventions for stress reduction by capturing knowledge on the dynamic inter-relationship of brain patterns related to stress.

The inclusion of SVM, Naive Bayes, and CNN machine learning models brings in complexity to the process of stress detection. Every model offers unique advantages and all together, they provides a holistic blueprint for profiling stress patterns in complicated brainwave signals. SVM, that can handle complicated data, Naive Bayes with simplicity and efficiency in probably classification and CNN with the hierarchical feature learning can make an integrated effective stress detection system. The use of SVM is motivated because it can work in high-dimensional feature space which is suitable for the complex patterns obtained from brainwave signals. Naive Bayes, as the term suggests, based on probability techniques and can support large feature sets which can aid in simplifying and fast classification. CNN, a longstanding model for image and sequence data processing has distinct proficiency in modeling spatial as well as temporal dependencies in brain wave data making the stress detection more enriched.

As we explore the inner-workings of this monster, it becomes obvious that the marriage of Brainwave Biofeedback with leading-edge machine learning has the potential to revolutionize how stress is managed. The flexibility of the system to personalized characteristics about stress response and the possibility for instant personalized interventions and support, and the effectiveness of joint SVM/Naive Bayes/CNN make this solution an intelligent, scalable approach addressing a never-ending demand over ever increasing concern.

This paper is organized as follows, with the detailed methodological and implementation aspects described in forthcoming sections along with an account of our experimental setup. brainwave assessment and predictive brain both of modules Centre for Studies in Rural Socio - Economic Life. Machine learning models, this work aims to not only progress the knowledge of stress detection, but also provide a stepping stone for disruptive and personalized interventions that address of unique needs individuals dealing with the modern challenges for living.

The objective of the proposed work is as follows:

- To understand how is EEG data is collected and processed.
- To develop an ensemble learning model to classify the acquired dataset into stressed and non-stressed classes.
- To further ensure the robustness of the generated model.

This paper has been organised as follows: Section 2 presents the detailed survey of existing works on the use of EEG to detect stress in human beings and what machine learning models have been already used and their merits. Section 3 gives the detailed description of the architecture being used in this study. Section 4 provides the performance metrics achieved by the model created for the study. Section 5 concludes the research work and explains the future scope of the study.

2 Related Work

In the paper Stress recognition using Electroencephalogram (EEG)[1] signal by TuerxunWaili, Yousif Sa'ad Alshebly, Khairul Azami Sidek and Md Gapar Md Johar, the authors suggest that EEG signals have a direct relationship with emotional alterations in the brain can help us identify and measure the amount of arousal in the brain. The brain waves are divided into different frequency bands, each associated with different states of brain activity. The typical frequency bands for brain waves are as follows:

1. Delta waves: 0.5Hz to 4Hz - observed during deep sleep and associated with unconscious bodily functions.

2. Theta waves: 4Hz to 8Hz - observed in a state of drowsiness and during meditation.

3. Alpha waves: 8Hz to 12Hz - observed in a state of relaxation and during light meditation.

4. Beta waves: 12Hz to 30Hz - observed in a state of active thinking, problem-solving, and decision making.

These frequencies are employed to study brain functions and could offer a glimpse into the psychological or emotional states of people. This also suggests that the power spectrum of brain beta rhythm over alpha as well as individual Alpha wave, is directly related to the stress levels, so a single band of waves (alpha band) can be used for identification of stressed human being. They discovered that under stress the ratio of beta to alpha wave power – which can be measured using EEG – increases. Although it was only a proof of concept to the method, the results from the volunteers revealed an obvious wave change to the algorithm. Hence the test can be applied for stress detection if the decision falls into 15.6% and 52.8 % of (Beta/Alpha).

In the study "Human stress classification using EEG signals in response to music tracks"[2] EEG signals were recorded and analysed using a commercially available four-channel brain sensing MUSE headband. The EEG data acquisition process involved several steps:

A total of 30 healthy subjects, including 15 males and 15 females, participated voluntarily in the study. The participants belonged to diverse cultural and educational backgrounds, with Urdu being their first language and ages ranging from 20 to 35 years. All participants had normal hearing power and no reported history of neurological disorder.

Nine audio music tracks in mp3 format were used as external stimuli for the stress classification experiment. The songs ranged from rock/ metal to electronic, rap, famous, patriotic, melodious, qawwali and ghazal tracks in English and Urdu. In each of the genres, the music tracks were chosen based on YouTube rating.

The EEG MUSE head-band was used to record brain signals, while the participants were listening to the music tracks. EEG was recorded at different time frames and state anxiety of participants was measured before and after listening to the music pieces.

The brain activity of 27 subjects was recorded using a four-channel brain sensing MUSE EEG headband in response to different language music tracks. The EEG signals were recorded before and during the presentation of music stimuli. The recorded data was analysed based on five features, including absolute and relative power, coherence, phase lag, and amplitude asymmetry.

The recorded EEG signals were pre-processed to remove noise before feature extraction and classification. The MUSE headband provided both raw and pre-processed EEG signals. A notch filter was applied to the raw EEG data to remove frequencies between 45 and 64 Hz. The pre- processed signal was obtained by over-sampling followed by down-sampling to yield an output sampling rate of 256 Hz, with 2uV (rms) noise. Active noise cancellation was achieved using an on-board driven right leg (DRL) circuit between the frontal electrodes and Fpz electrode.

Five groups of features were extracted from pre- processed EEG signals from four channels (AF7, AF8, TP9, TP10) and five frequency bands (delta, theta, alpha, beta, gamma) using fast Fourier transform (FFT) and other techniques. The persisted features were then employed for stress classification with various classifiers e.g. SMO, SGD, LR and MLP.

In the present study, a comprehensive methodology was adopted to record and analyse EEG signals recordings following music exposure, in order to facilitate HSCA and investigate the effects of different language music tracks, musical genres and differences among male/female on stress reduction via listening to these sequences.

As mentioned, three classifiers have been compared which include (SMO) sequential minimal optimization, stochastic gradient descent (SGD), logistic regression (LR), and multi-layer perceptron (MLP). The findings showed that classifier LR produced superior performance compared to classifiers SMO, SGD and MLP in both two-class, three class stress classification problems with highest reported correct rate of 98.76% and 83.33%, respectively. The paper,” Machine Learning-Based Stress Level Detection from EEG Signals” [3], proposes a model of identifying stress levels via EEG signals. The research adopted a database of high-stress and low-level stress EEG recordings. The approach adopted included pre-processing of the signals to eliminate noise and feature extraction based on the wavelet transform. Stress levels were classified using the 4 classifiers SVM, KNN, Naïve Bayes and LDA.

Results The lowest accuracy rate to classify the depression was recorded for Naïve Bayes with 81.7% (Table 1), which were higher comparing to KNN with 86.3%), followed by LDA (90.0%) and SVM, obtaining the highest degree of accuracy up to 91.0%. The framework also performed better than existing research, as it attained the highest accuracy of 91.0% when compared to the current benchmark which is 78.57% using SVM classifier.

In summary the presented approach showed that EEG is effective for stress detection. The max accuracy was achieved with SVM classifier and wavelet transform method as feature extraction. The contribution of the study to stress detection is a valid and accurate method. Further studies might investigate the application of other classifiers and feature extraction methods in order to increase the accuracy of stress level classification based on EEG signals.

The work presented by “Enhancing biofeedback-driven self-guided virtual reality exposure therapy through arousal detection from multimodal data with deep learning” is a concept of treating anxiety treatment with VERT based on the EEG monitors. By applying machine learning models, the researchers became able to identify anxiety-induced arousal and then prompt calming interventions people could use to alleviate distress. The paper additionally addresses issues in the efficient ML models and parameters selection with arousal detection, pointing to a potential pipeline to address the model selection problem. VRET with the biofeedback model was developed for VRET, which enables feedback of heart rate and brain laterality index from multimodal sources for psychological intervention to reduce anxiety.

The review used various machine learning models to detect emotions or stress for diverse phobia types. For example for Acrophobia SVM, RF and K-NN was used giving a 42.6%, 99% and 89.5%, respectively. For stress, K-NN, SVM and Naïve Bayse was employed with result of accuracy or performance 71.76%, 90% and 81.7%. The paper also provides an overview of how well each ML model does on EEG data. The work employed a number of machine learning models such as Quadratic Discriminant Analysis (QDA), Gaussian Naïve Bayse (GNB), Support Vector Machines (SVM), Multilayer Perceptron (MLP), AdaBoost (ADB), K-Nearest Neighbours (KNN), Decision Tree and Random Forest. The accuracy of the models were tested on the SWELL dataset as well as EEG dataset.

Here, the modified SVM algorithm for detecting stress lever Using EEG signals by Tang et al., called as “Modified Support Vector Machine for Detecting Stress Level Using EEG Signals” [5] is being further developed here with the help of one evolutionary metaheuristic Known as Modified Whale Optimization Algorithm (MWOA) to find best kernel in SVM classifier. MWOA is based on hunting mechanism of the humpback whales and a metaheuristic optimization technique. It is a method for enhancing the generalization ability of SVM classifier in selecting a kernel function.

Apart from the modified SVM, this research combines a number of algorithms related to preprocessing, and feature extraction with selection on noisy EEG. These algorithms are the Non-Local Means (NLM) method, Discrete Cosine Transform (DCT), and Modified Binary Particle Swarm Optimization (MBPSO) for feature selection. The selected features for recognition of stress level are determined by the use of MBPSO optimization, a modification of the standard particle swarm optimization algorithm with binary value.

The purpose of incorporating these algorithms is to improve the accuracy as well as to promote efficiency in recognizing stress with EEG signals. The modified SVM combined with MWOA and other algorithms can enhance the feature selection and classification of the stress detection system.

According to an article,” EEG based interpretation of human brain activity during yoga and meditation using machine learning: A systematic review” [6], the authors point out that the use of machine learning methods in processing of EEG signals for understand how yoga and meditation influence human cognition. They identify the three key steps associated with classifying brain waves during meditation: data acquisition and noise filtering, feature selection, and classification. These stages deepen the insights of benefits of yoga and meditation, for such relief against anxiety, fatigue reduction, inducement of emotionally positive states, and internalized attention.

This review highlights the necessity of the 20-year time span covered in the literature search that provided 120 articles pertinent to this subject. The selection and exclusion criteria were clearly defined in making it possible to extract the relevant articles based on research title and area of interest. The authors highlight the importance of further probing EEG data to reveal the underlying mechanisms by which yoga and meditation contribute to these endeavors.

Moreover the review recognizes heterogeneity of methodologies used in the literature such as EEG acquisition equipment, and analysis on posture, breathing, meditation practice targeting changes in structural brain activation. This diversity emphasizes the multidimensional aspect of this type of

EEG-based research, and the necessity for uniform methods to enable comparison between and synthesis of study results.

Lastly, this SR offers an overview of the different methods adopted, findings yielded, and implications drawn from studies of yoga and meditation that are based on EEG. It highlights the potential machine learning techniques have for further elucidating how these practices influence brain activity and subjective mental health. The review further highlights the importance of exploring and standardizing methods to contribute to this growing area for research.

The article "A novel EEG for alpha brain state training, neurobiofeedback, and behaviour change" [7] investigates an EEG headband, for real-time feedback of alpha brain waves during mindfulness meditation and positive affirmation tasks. Both thereatological observations and eral data derived fro callus presented here offer the potender significance for understanding the role applications of this mechanism to the development and design for change in health and well-being.

The results of the research are promising, with the EEG headband being sensitive in measuring variances on brain waves responses between attention exercise and alpha brain state exercises. The elevation in theta and alpha frequency, as well as a decrease in the amplitude and frequency of delta observed here agrees with previous research, suggesting educational and mindfulness applications for this technology. The study also illustrates the promising use of the EEG headband as a biofeedback tool to train alpha brain states for those interested in altering their behaviour, such as focusing attention on diet change, exercise, stress/reducing anxiety and depression.

Qualitative observations of the study suggested that participants achieved a relaxed state easily under the alpha brain state exercise, and meditation and attention scores had altered based on specific cues and tasks presented. Our finding that this steady and strong rhythm is one with sensitivity toward different levels of (high/low) alpha brain wave activity, and to be able to easily cluster subjects according their brain waves contributes again to the high potential use of this technology in personalized remedial treatments, neurofeedback training etc.

However, this study also found limitations such as some of the subjects' concerns about positive affirmation which surfaced in the study imply that another round of revision and instruction would be warranted on this front. The accuracy of the "meditation" and "attention" measurements reported by the EEG headband software were also doubted, reinforcing the need to validate and optimize measurement metrics for actionable and reliable feedback.

Overall, the study offers an important evidence that the EEG technology might have a potential as neurobiofeedback tool in promoting alpha brain states and inducing behaviour change. The results encourage further investigation of this technology in larger controlled intervention studies, comparing neurobiofeedback data with pen-and-paper measures of mindfulness, psychological wellbeing, and physical health. More research and development in this space could change the game for tailored interventions for behaviour change and mental health, by providing: new opportunities for human resources training and sustainable Subconscious-driven behavior change.

In conclusion, the study serves as a foundation for continuing research into EEG technology as an effective supplement in enhancing alpha brain states and driving behavioral change leading to potential future applications across multiple domains including healthcare, education and personal development.

The article ‘A survey of machine learning techniques in physiology-based mental stress detection systems’ highlights the significance of stress on personal health and societal costs. The stress not only imposes feelings of distress on the medical family but also adversely affects their overall quality of life (QOL) at personal, professional, and social fronts. The negative influence of mental stress on physiology, psychology, physical health and overall wellness demonstrates the importance of effective stress detection systems. Such developments as the introduction of machine learning and wearable technology in healthcare appear to be breakthrough with social effects. A promising future perspective is suggested to be the utilization of physiological data to predict mental stress.

It's an all-inclusive review, covering physiological data collection, emotion detection systems based on machine learning, stress detection systems based on machine learning, evaluation measures etc., challenges in development of the system and wide ranging applications. Work contributions of the authors are clearly defined; the first author did conceptualization, data curation, formal analysis, methodology, visualization and draft writing whereas second author contributed towards study execution as well technical assistance and overall supervision.

Research potential of the study is emphasized for other researchers because it clearly represents a profile and value of the field. Conclusion This work which we have presented is important with respect to the problem of generalized, efficient and robust stress detection systems. The call for using physiological data in predicting mental stress made by the authors resonate with the increasing interest on machine learning over wearable and other healthcare type of datasets to classify groups and determine relationship.

In summary, the importance of developing stress detection systems are re-emphasized and also indicates the promise that machine learning holds in fighting this crucial societal and personal health problem. The authors want to use this review to guide and motivate other researchers in this area so we can establish more efficient stress detection systems.

They presented a paper "Biofeedback Based Computational Approach for Working Stress Reduction through Meditation Technique " [9] that describes an innovative mechanism of stress detection and classification with GSR (galvanic skin response) and image based biofeedback assisted mindfulness meditation. Objective: The present work is seeking to introduce a computational tool for decreasing working stress by the means of mediation methods that can be used in controlling the stress and mental health.

The results of the research indicate that the developed approach presents good scores on stress detection and classifying. The study separates stress into two states and implies the possibility of using survey step #1 for discriminating other states of stress obtained by quantitative measurements in further research. GSR sensors connected to users’ machines through wires as well as computer games that rely on such sensors are both recognized as cumbersome, leading to a suggestion of developing wireless GSR sensors incorporated into widely used products achieving better usability.

Accuracy assessment of the approach shows quite satisfactory levels of precision (more than 60percent accuracy for all three stress states). The results also depict low percent relative errors, which shows that the proposed method is successful in quantifying the stress levels. In addition the study utilizes one-way ANOVA tests to demonstrate (and confirm) that there is indeed a significant statistical similarity and relationship between various stress states, thus an added constructive proof of the effectiveness of the approach.

The study is multi-method with a mixed qualitative and quantitative methodologies to ensure validity of findings. Observational and qualitative analysis of questionares answers and readings of Galvanic Skin Response signal, support here to the distinction between "phases" of testing as well as the non occurance of external stressors affect response in these testing situations. It also illustrates the significant impact image-based coverage had on positive.

Biofeedback regarding process of meditation as reported by participants. The stimulation signal is preprocessed and features are then extracted from it; they use the area under the curve (AUC) as a way to look at GSR signals. The AUC is used to evaluate the levels of skin conductance activity which provides valuable insights regarding psycho-physiological changes due to stress. The stages of data collection as part of the study included participants' relaxation, pretest questionnaires, capturing GSR while performing each tasks designed to evoke stress responses 16 and completion of posttestiousn questionnaires.

Finally, the paper proposes an empirical biofeedback-based computational model for reducing working stress through meditation exercises. Research results indicate that this method has the capability for accurate stress detection and classification, which can be applied in reducing stress and promoting mental health. The incorporation of GSR wireless sensors and image- based biofeedback in routine devices may provide easy solutions for people who want to reduce stress at work and to improve health, at the same time.

Research provided in: "Modeling Mental Stress Using a Deep Learning Framework" [10] provide an exhaustive study on the application of WBDAN and DL approach to simulate, estimate the mental stress. Here we take advantage of the fact that physiological and psychological parameters vary as a function of stress to develop a non-invasive method of assessing stress.

The paper starts with a discussion of the physiological effects that are brought on by stress, including the release of hormones such as cortisol and the changes that long-term stress has on various system of the body. It also analyzes the less invasive parameters, such as heart rate variability, respiration and skin conductance, are good indicators of effort. This lays the path for subsequent discussion of experimental procedure and results.

The experiments in the paper are two-staged, where in stage 1 traditional lower body physiological signals are captured and in stage-2 neural signals from upper body. Cognitive challenges designed to put the participants in a state of stress, and the physiological data of subjects are collected and processed here. The work uses a deep learning approach to analyse the data collected and identify the existence and degree of mental stress.

The findings from the study indicate that the model that was proposed is effective in accurately detecting and classifying stress based on physiological and neural signals. The proposed deep learning architecture along with feature selection analysis, in the end becomes sufficient and effective for stress vs. n- Stress classification accuracy. Moreover, the work studied the contribution of neural parameters for further improving the accuracy of our model that offers an important insight into cerebral as facilitating data in stress detection.

Finally, the paper concludes with a summary indicating that wireless body area network and deep learning methods offer a viable non-invasive efficient solution for mental stress modeling and monitoring. The results have implications for practical applications in stress coping, wellness, and healthcare. Based on the use of state-of-the-art technology and physiology, this study opens up some new perspectives in coping with mental stress and provides a groundwork for future research and application under varieties of conditions.

A Hybrid Feature Selection Method for EEG-based Emotion Recognition [11] introduces such an impressive technique for emotion detection that deal with EEG signals. The objective of the study is to overcome problems of feature selection and classification in EEG based emotion recognition. The proposed method leverages statistical and frequency features to provides a pool of hybrid features, on which Boruta algorithm is employed as the feature selection approach. The extracted features are used to train a k-Nearest Neighbour.

The experimental study is based on a dataset, where several participants' EEG signals are recorded during different emotions. Results show that the proposed framework is able to appropriately classify emotions. The average accuracy obtained by the proposed approach is 73.38%, it can be seen that the PCA + k-NN, LDA + k-NN (accuracy 65.62%) and all Features + k-NN (accuracy 69.26%).

The study also emphasizes the difficulty in generalizing EEG signals across different subjects. Every subject has distinct response profiles, and a generic pattern cannot be applied to all data. Furthermore, samples for each emotion are imbalanced. For these problems, we use SMOTE algorithm to balance the dataset.

Comparison with related methods A quantitative comparison of the experiments is shown in Table 2. The results show that, for most individual datasets, our model achieves better performance compared to other methods. The advantage of the new method is also verified by a one-way ANOVA tests, showing a significant difference for three methods.

Finally, a hybrid feature selection method for EEG-based emotion recognition is proposed by combining statistical and frequency domain features. The proposed method outperforms other counterparts, with the accuracy of 73.38%. It is a new proposal in emotion recognition where problems of feature selection and classification are taken into account in the EEG signals domains. The results offer implications for future work in this domain, and underscore the need to address individual participant responses as well as bias in data set affecting emotion recognition studies.

The work "Towards multilevel mental stress assessment using SVM with ECOC: an EEG approach" [12] proposed the classification of several classes of codified mental attention levels, classifying through EGG signals. Participants performed a mental arithmetic task with different stress levels elicited by time pressure and negative feedback. EEG signals in prefrontal cortex were analyzed and demonstrated that power of alpha rhythm decreased as stress levels increase. A right-dominant prefrontal cortex activation during stress was also reported by the study. A multiclass SVM with ECOC reached an average accuracy of 94.79% in the classification of stress levels. The limitations are that the sample was only comprised of males and we included a small number of EEG channels. The results implicate putative gender effects on stress reactivity and the importance For additional electrode for improved localization of mental stress.

The research revealed that Mindfulness Training (MT) can have a noticeable impact on our brain's functioning and structure, specifically within the attentional and emotional networks. Using EEG data, the study tested for connectivity and level of activation in the brain before and after MT. Results indicated that MT enhanced connectivity in the alpha and beta frequency bands, correlates with attention and cognitive control. This result was further confirmed by the observation that effects of

MT on connectivity also occurred within the delta and theta bands, wavelength intervals known to be implicated in mind-wandering as well as in negative emotions associated with mind-wandering.

The authors also noted that MT seemed to be more effective in depressed versus non-depressed individuals. The mood and the symptoms of depression were decreased clearly in patients with comorbid depressive episode, treated with MT. The result indicates the efficacy of MT for depression, especially in resistant cases to typical care and medications with or without psychotherapy.

The spiking Neural Network model of the study designed a new neuro-biological explanation for brain functioning in depression and its adjustment by MT. The model allowed to see the transition between EEG sub-bands before to after instruction, thus a measurable reflection of changes within brain activity. Additionally, the model enabled us to monitor connectivity and activation in brain that helped in understanding of neural mechanisms mediating effects of MT.

The study has implications for understanding the neurobiological profile of MDD who benefit from MT, showing that MT may change brain functioning, and offering promising directions for treatment targeting depressed individuals. The study illustrates the need for mechanistically interpreting MT that offers a new way of measuring brain function in depression. The implications of the present study for the development of treatment to depression as well as to understanding brain underpinnings of mindfulness are considerable.

3 Proposed Work

This section provides the detailed description of the proposed technique regarding the approach for the brainwave biofeedback for stress detection. The overall flow of the proposed work is given in figure 1.

The EEG data is often collected and represented in three variations, namely:

- Time domain
- Frequency domain
- Time-Frequency domain

In time domain, EEG signals are represented as voltage fluctuations over time. The raw EEG data is recorded as a series of voltage measurements over time. This allows to observe the changes in electrical activity over time. The frequency domain constitutes decomposing raw EEG data into different frequencies using a mathematical transformation called Fast Fourier Transform. This helps in decomposing the activity into frequency bands as delta (0.5-4 Hz), theta (4-8 Hz), alpha (8- 13 Hz), beta (13-30 Hz), and gamma (30+ Hz). Different bands are associated with different brain states and functions. Time-frequency analysis involves the study of how the frequency content of the signal changes over time. This method contains common techniques such as Short-Time Fourier Transform and spectrogram analysis.

In this work, an open-source dataset, available on Kaggle, containing all the three types of data is used to conduct and in-depth study of how the model function on each type of dataset domain. The preprocessing of the dataset is a crucial step to enhance the quality and remove unwanted artifacts and noise. This helps in creating a dataset for further analysis.

3.1 Preprocessing

Initially, a preprocessing approach is carried out on the dataset in which the following steps are performed:

Noise removal: Raw data is often mixed with noise or unwanted artifacts that can distort and malform the true underlying patterns.

Artifact removal: EEG recordings can be affected by artifacts such as eye blinks, muscle contractions or even electrode drift. Preprocessing techniques, including artifact rejection and correction algorithms are used to mitigate such artifacts.

Normalization: The data collected may be collected across different sessions resulting is variation in physical aspects such as the test environment, test subject's physical state etc. Therefore, to standardize the data, to make it comparable across different conditions and individuals, normalization is used.

Filtering: To isolate specific frequency bands of interest while ignoring the unwanted frequencies, a bandpass filter is used to focus on a particular frequency range associated with different brain region and activity.

Standardization: The process of rescaling the feature by transforming them to have a mean of 0 and standard deviation of 1.

Algorithm 1: Preprocessing of EEG Signals
Input: Raw dataset from Kaggle Step 1: Removal of Noise Step 2: Removal of artifacts Step 3: Normalization Step 4: Standardization Step 5: Filtering Step 6: Reshaping
Output: Pre-Processed data

Reshaping helps in creating a reshaped dataset which is commonly used while dealing with sequential dataset.

3.2 Models Used

From the previous studies a lot of information was gained as to how different machine learning model performed for the different types of datasets. Almost all the studies used real-time data collected from volunteers and hence in the need of protection of the identity of the subjects no information other than the type of data collected was disclosed about the datasets. The dataset being used in this study is a completely new and has not been tested before, therefore models needed to be tested from scratch. From the existing studies a lot of models were selected and tested against the dataset. The models tested along with their accuracies are as follows:

It was noticed that XG Boost and Logistic regression were giving the highest accuracy among all the models yet it was not sufficient to be called as a success. Therefore, genesis of an idea of creating an ensemble model took place.

Particle swarm optimization was chosen as the method of optimizing the ensemble model created and XG Boost and Logistic regression were kept as base models as they gave highest accuracy on their own. Grid search was also used to tune the hyper parameters for the models used.

Ensemble Learning: It is a machine learning technique involving the combination of predictions of different machine learning models to create a stronger and robust model. The basic idea is to combine the strengths of multiple models, the overall performance can be improved and weaknesses can be mitigated and removed. Ensemble method often helps in achieving better predictive accuracy, stability and generalization on a given task.

Particle Swarm Optimization: it is a computational optimization technique inspired by the social behaviour of groups of birds and fish namely their movement as a group. Developed in the 1990s by James Kennedy and Russell Eberhart, it is a population-based algorithm that iteratively searches for a solution space to find optimal or near optimal solution.

Grid Search: It is used to find the optimal set of hyperparameters for a model. It uses a predefined grid of hyperparameters and for each combination of hyperparameters the model is trained and tested. Although being computationally exhaustive, it provides a systematic approach for finding optimal hyperparameters.

After training XGBoost, Logistic Regression, MLP and LDA models from the time domain data and testing we obtained that 4 Models Ensemble comprising of XGBoost, LR, MLP and LDA resulted in maximum accuracy.

And now to go into detail about those models:

XGBoost: It is an efficient and effective machine learning algorithm for prediction. It implements gradient boosting technique which works on ensemble process by building multiple weak learners in a stepwise manner to rectify the errors of its predecessor models. It also contains regularization method to manage model complexity and prevent overfitting and tree-pruning for better generalization.

Logistic Regression: It used to perform binary classification. The algorithm employs the sigmoid activation function to turn the linear combination of input feature and weights into probability between 0 and 1. Its hypothesis function will give a probability prediction, and that forms the decision boundary to separate data points.

Multilayer Perceptron: It is a fundamental neural network architecture capable of learning complex relationship in data. It consists of multiple layers of interconnected nodes also called neurons. It is highly efficient in capturing ang recognizing intricate patterns and non-linearities. Trained through backpropagation and gradient descent, they adapt and optimize internal parameters to enhance their performance.

Linear Discriminant Analysis: It is a powerful technique for dimensionality reduction and classification. By maximizing the distance between class means while minimizing in-class variance, LDA finds the most discriminative feature space. It is widely used in pattern recognition and is highly simplistic and also helps in reducing dimensionality while preserving class information.

3.3 Steps Followed

Initially all the models mentioned above were trained and tested and evaluated on their own resulting in their individual accuracies. This gave an overview of how every model was performing on the given dataset. After this step an ensemble model was created to test how different models would work with one another. Weighted average ensembling is used to merge the different models together so as to take the best parts of all the models.

In the first phase of testing a set of three models sequentially were taken to create the ensemble Precision

Precision: It is a key evaluation metric in machine learning which measures the accuracy of positive predictions made by model, using the ratio of correctly predicted positive instances among all instances predicted as positives.

$$Precision = \frac{TP}{TP + FP}$$

Recall

It is the measure of a model's ability to correctly identify all relevant instances from a given class. A high recall score indicates that the model is effective at capturing a significant portion of the positive instances in the dataset model and their accuracies were tested. From this testing a satisfactory accuracy could not be achieved, even after hyper parameter tuning, hence a decision to increase the number of models in the ensemble was made. Now a set of 4 models was taken subsequently and tested. From this testing the set XGB, LR, MLP and LDA gave the highest accuracy along with hyper parameter tuning. For this set PSO was applied and different values for particles number and iterations was chosen so as to get the highest amount of accuracy for the model.

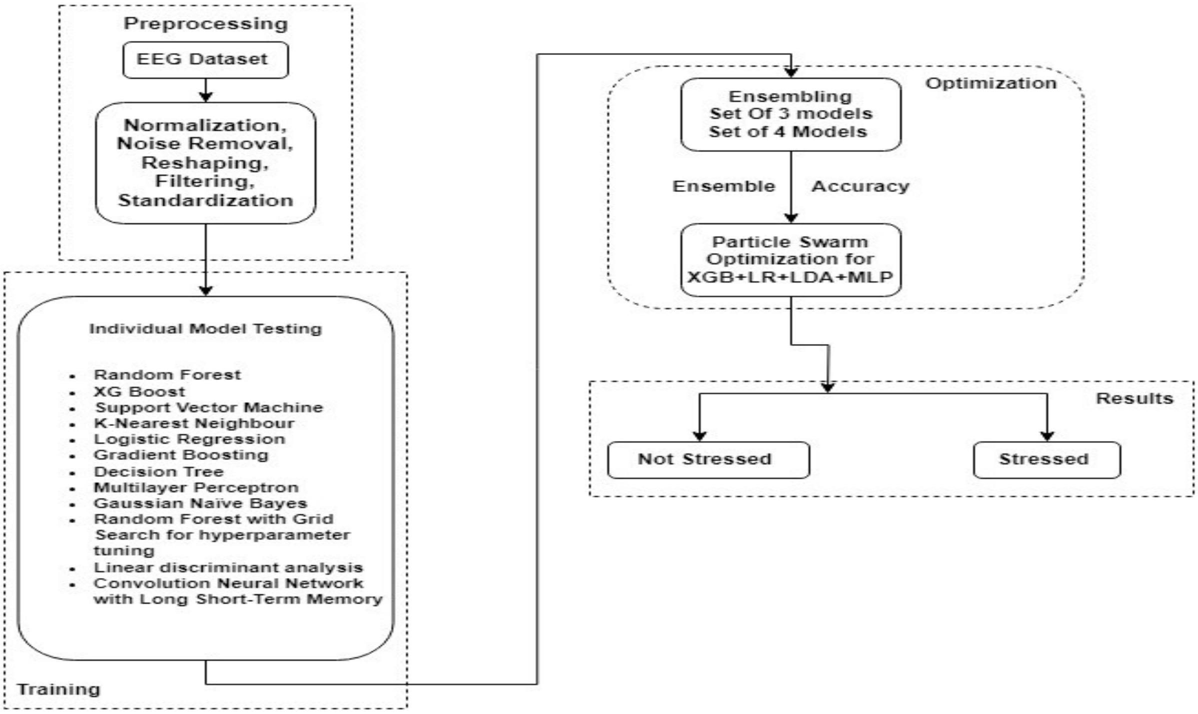

Fig 1. Overall Flow of the proposed technique

4 Experimental Analysis

4.1 Performance analysis

This section provides the performance study of the proposed system. The analysis is performed via Accuracy.

Accuracy

It is common evaluation metric used to measure the performance of a classification model. It represents the proportion of correctly classified instances to the total instances in the dataset.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Table 1: Experimental results of the all models

Si. No.	Model	Accuracy (in %)
1.	Random Forest	66.52
2.	XG Boost	69.2
3.	Support Vector Machine	65.23
4.	K-Nearest Neighbour	59
5.	Logistic Regression	68.5
6.	Gradient Boosting	59

7.	Decision Tree	61
8.	Multilayer Perceptron	66
9.	Gaussian Naïve Bayes	53
10.	Random Forest with Grid Search for hyperparameter tuning	65
11.	Linear discriminant analysis	66
12.	Convolution Neural Network with Long Short-Term Memory	52.5

Table 1 presents the classification accuracy achieved by various machine learning and deep learning models for the considered prediction task. Accuracy is expressed as a percentage and represents the proportion of correctly classified instances among the total samples.

Among all the evaluated models, XGBoost achieved the highest accuracy of 69.20%, demonstrating its effectiveness in capturing complex relationships within the dataset through gradient-boosted decision trees. Logistic Regression followed closely with an accuracy of 68.50%, indicating that a relatively simple linear model can perform competitively when the underlying data exhibits linear separability. Random Forest attained an accuracy of 66.52%, benefiting from ensemble learning through multiple decision trees and reducing overfitting compared to a single decision tree.

The Multilayer Perceptron (MLP) and Linear Discriminant Analysis (LDA) achieved accuracies of 66.00%, while the Support Vector Machine (SVM) obtained 65.23% accuracy. These results suggest that both linear and nonlinear classification techniques provide moderate predictive performance for the dataset.

The Random Forest model with Grid Search-based hyperparameter tuning achieved an accuracy of 65.00%, which is slightly lower than the default Random Forest configuration. This indicates that the tuned parameters did not significantly improve the model's generalization performance for this specific dataset.

Tree-based methods such as Decision Tree and Gradient Boosting produced accuracies of 61.00% and 59.00%, respectively. Similarly, the K-Nearest Neighbour (KNN) classifier achieved 59.00% accuracy, suggesting limited effectiveness in handling the underlying data distribution.

The lowest performance was observed for the Convolutional Neural Network with Long Short-Term Memory (CNN-LSTM) model, which achieved 52.50% accuracy, followed closely by Gaussian Naïve Bayes with 53.00% accuracy. The comparatively lower performance of CNN-LSTM may be attributed to insufficient data volume or the absence of strong spatial-temporal characteristics in the dataset, while Gaussian Naïve Bayes may have been affected by its assumption of feature independence.

Overall, the results indicate that ensemble learning approaches, particularly XGBoost and Random Forest, consistently outperform individual classifiers and deep learning architectures for the given dataset. The highest accuracy achieved by XGBoost suggests that boosting-based methods are more capable of modeling complex feature interactions and provide superior predictive performance compared to traditional machine learning and deep learning models in this study.

5 Conclusion

In this paper we proposed an ensemble learning method to predict the stress in a human using EEG dataset. At first 12 machine learning models were used individually and their scores noted. After this these models were used in sets of 3 and 4 to create ensembling models. After this the ensemble of XGB, LR, MLP and LDA gave the highest score and hence was further optimised using Particle Swarm Optimisation. The analysis of performance was done using metrics such as accuracy, precision, recall, F1 score etc. and it is found that this ensemble method is a better way to tackle the frequency domain EEG data for stress detection.

In future, this work can be enhanced by implementing some other algorithms which will make this study useful for even time and time- frequency domain EEG dataset. Furthermore, real time monitoring can also be implemented which will be much more effective in control and monitoring of stress. This will all help in creating a mobile unit for real-time stress monitoring.

References

1. TuerxunWaili, Sa'ad Alshebly, Y., Azami Sidek, K., & Md Johar, M. G. (2020, March 1). Stress recognition using Electroencephalogram (EEG) signal. Journal of Physics: Conference Series, 1502(1), 012052. https://doi.org/10.1088/1742-6596/1502/1/012052

2. Asif, A., Majid, M., & Anwar, S. M. (2019, April). Human stress classification using EEG signals in response to music tracks. Computers in Biology and Medicine, 107, 182–196. https://doi.org/10.1016/j.compbiomed.2019.02.015

3. Nirabi, A., Rahman, F. A., Habaebi, M. H., Sidek, K. A., & Yusoff, S. (2021, August 23). Machine Learning-Based Stress Level Detection from EEG Signals. 2021 IEEE 7th International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA). https://doi.org/10.1109/icsima50015.2021.9526333

4. Rahman, M. A., Brown, D. J., Mahmud, M., Harris, M., Shopland, N., Heym, N., Sumich, A., Turabee, Z. B., Standen, B., Downes, D., Xing, Y., Thomas, C., Haddick, S., Premkumar, P., Nastase, S., Burton, A., & Lewis, J. (2023, June 21). Enhancing biofeedback-driven self-guided virtual reality exposure therapy through arousal detection from multimodal data using machine learning. Brain Informatics, 10(1). https://doi.org/10.1186/s40708-023-00193-9

5. Gupta, R., Alam, M. A., & Agarwal, P. (2020, August 1). Modified Support Vector Machine for Detecting Stress Level Using EEG Signals. Computational Intelligence and Neuroscience, 2020, 1–14. https://doi.org/10.1155/2020/8860841

6. Kora, P., Meenakshi, K., Swaraja, K., Rajani, A., & Raju, M. S. (2021, May). EEG based interpretation of human brain activity during yoga and meditation using machine learning: A systematic review. Complementary Therapies in Clinical Practice, 43, 101329. https://doi.org/10.1016/j.ctcp.2021.101329

7. Stinson, B., & Arthur, D. (2013, August). A novel EEG for alpha brain state training, neurobiofeedback and behavior change. Complementary Therapies in Clinical Practice, 19(3), 114–118. https://doi.org/10.1016/j.ctcp.2013.03.003

8. Panicker, S. S., & Gayathri, P. (2019, April). A survey of machine learning techniques in physiology based mental stress detection systems. Biocybernetics and Biomedical Engineering, 39(2), 444–469. https://doi.org/10.1016/j.bbe.2019.01.004

9. Perera, J. A. P. H., Perera, P. M. C., Rathnarajah, L. M., & Ekanayake, H. B. (2016, September). Biofeedback based computational approach for Working Stress reduction through meditation technique. 2016 Sixteenth International Conference on Advances in ICT for Emerging Regions (ICTer). https://doi.org/10.1109/icter.2016.7829910

10. Masood, K., & Alghamdi, M. A. (2019). Modeling Mental Stress Using a Deep Learning Framework. IEEE Access, 7, 68446– 68454. https://doi.org/10.1109/access.2019.2917718

11. Hasan, & Kim. (2019, December 13). A Hybrid Feature Pool- Based Emotional Stress State Detection Algorithm Using EEG Signals. Brain Sciences, 9(12), 376. https://doi.org/10.3390/brainsci9120376

12. Al-shargie, F., Tang, T. B., Badruddin, N., & Kiguchi, M. (2017, October 18). Towards multilevel mental stress assessment using SVM with ECOC: an EEG approach - Medical & Biological Engineering & Computing. SpringerLink. https://doi.org/10.1007/s11517-017-1733-8

13. Doborjeh, Z., Doborjeh, M., Taylor, T., Kasabov, N., Wang, G. Y., Siegert, R., & Sumich, A. (2019, April 23). Spiking Neural Network Modelling Approach Reveals How Mindfulness Training Rewires the Brain. Scientific Reports, 9(1). https://doi.org/10.1038/s41598-019-42863-x

14. EEG features dataset for stress classification