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Wavelet Transform and Genetic Algorithm Optimization For EEG Stress Detection

Sangita Ajit Patil[1*,2], and Ajay N. Paithane[3]
[1] Asst. Professor, PCCoE Pune, India - 411044,*
Orcid id: 0009-0006-7985-6486
2Research Scholar, RSCoE Pune, India – 411033.
3Research Guide, Assoc. Professor, D.Y.Patil International University, Akurdi, Pune, India – 411035,
Orcid id: 0000-0002-1063-0570
*Corresponding author's Email: sangita.patil@pccoepune.org

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Abstract: Accurately detecting mental stress through electroencephalography (EEG) signals is challenging due to artifacts. Moreover, achieving optimal system performance in mental stress detection requires efficient processingand prominent feature extraction techniques. This study explores signal-denoising methods for stress detection using EEG signals, investigating various pre-processing and feature extraction techniques, including finite impulse response filters, wavelet transforms, and empirical mode decomposition. The comparative analysis underscores wavelet methodology as particularly effective for extracting stress-related features, achieving an 81.7% accuracy rate with support vector machines. Integration of optimized feature selection with genetic algorithms significantly improves model performance, yielding a notable 87% accuracy rate based on experimental findings. The study offers a practical framework for constructing efficient machine-learning models validated through MATLAB and Raspberry Pi implementations. It underscores their practical utility in real-world applications, especially in EEG-based stress detection methodologies.

Keywords: Electroencephalography (EEG), Empirical mode decomposition (EMD), Finite Impulse Response (FIR), Intrinsic Mode Functions (IMFs), Wavelet Transform (W.T.)

Introduction

This research addresses chronic stress as a widespread societal issue impacting mental health, aiming to utilize digital technology and EEG for early detection and management of stress to prevent associated disorders. [1-3].Consequently, EEG signals are commonly used in research to investigate stress-related brain activity. However, EEG signals are susceptible to noise from diverse sources and electrical interference [4,5]. This noise can corrupt EEG signals, posing difficulties in extracting meaningful features. Pre-processing is an essential phase in EEG analysis, which reduces noise and improves data quality by applying various pre-processing techniques, such as filtering and adaptive thresholding. Wavelet transforms as per application [6,7].The subsequent stage involves feature extraction, which identifies and quantifies distinct features in EEG analysis, such as power spectrum density, time-frequency patterns, and event-related potentials. Feature selection will be dependent on the application. Prominent features must be extracted from the denoised EEG signal to construct a novel stress detection system. This study investigates the mean, entropy, power, and energy of alpha and beta waves in an EEG signal.

Section 2 elaborates on a literature survey about mental stress detection. Section 3 discusses the challenges of mental stress detection systems and methodology. Section 4 elaborates on the comparative evaluation of different pre-processing and feature extraction techniques. Section 5 of this paper explores dimension reduction techniques like genetic algorithms. Section 6 demonstrates Wavelet-GA Fusion-based Enhanced Mental Stress Detection via EEG, and section 7 shows the implementation of Raspberry Pi, offering valuable insights for reliable stress detection.

2. Literature Review

Education, employment, and driving stress can be monitored with EEG to prevent health complications. Mental stress detection research emphasizes the difficulty of removing real-time data noise and distortions from stress detection systems [8,9].The research [10] proposes WOSG filtering to remove motion distortions from EEG recordings. This work uses percentage change in correlation coefficients to assess the performance of the suggested WOSG filtering technique. The results showed that the suggested WOSG technique improves EEG signal denoising. Furthermore, researchers observe that WOSG can also effectively remove noise from other physiological indicators. These discoveries enhance the progress of EEG signal processing methods, showcasing the effectiveness of the WOSG approach for improving the quality of EEG recordings. This paper [11] describes motion artifacts in biological signals that can impair EEG-based neuro-engineering systems. They provided the optimal LoG filter and improved EMD to remove motion artifacts from EEG records. Researchers split an EEG signal with noise into intrinsic mode functions (IMFs), which they use to recreate the denoised signal. The research [12] guides researchers in utilizing EEG measurements and computing various cognitive significance using EEG features. Statistical measures include mean, median, maximum- minimum difference, root-mean-square, standard deviation, variance, kurtosis, and total zero cross number. The fundamental aim of this research is to improve mental health. For this purpose, researchers develop machine learning algorithms to predict and detect an individual's stress levels accurately. The research paper [13] presents a system for evolutionary mental stress detection using EEG signals. Long-term stress exposure might cause significant health issues. Non-invasive approaches for stress detection need improvement to enhance predicted accuracy and dependability. Early stress detection is essential in scientific studies to prevent adverse effects on health, so the significance of this research paper is to provide a comparative evaluation of different pre-processing and feature-extracted technologies along with optimized feature selection methods to protect an individual's well-being and minimize potential damage to their health.

3. Challenges and methodology

Due to subject movement or activities, most biosignals are sensitive to noise or artifacts. This identified gap demands the development of an effective signal-denoising technique. Thus, the identified challenge is to remove artifacts and noise, and ensuring data accuracy is the most challenging aspect of developing any stress detection model, similarly, analyzing abundant sensor information results in high-dimensional feature space. As the size of feature vectors is large compared to the number of training instances, the model is prone to produce poor performance [14]. Updated feature selection and mapping techniques are required to handle high-dimensional physiological data and solve this problem. The prime objective of such techniques is to reduce the dimension of feature space. Thus, a primary challenge in stress detection involves extracting appropriate features from physiological signals. Pre-processing and feature extraction are crucial for analyzing EEG signals in mental stress detection. Pre-processing increases data integrity by eliminating noise and artifacts. Feature extraction is the process of discovering and measuring discrete data patterns. Researchers can use these patterns to differentiate between various levels of stress. Multiple approaches, such as filtering, wavelet, and EMD [15], can be used to build a more accurate and reliable proposed system for stress detection.

In this scientific study, pre-processing methods like FIR filtering, wavelet transform, and EMD are used to eliminate unwanted noise and isolate alpha and beta frequency effectively ranges closely associated with stress, as shown in Figure 1.

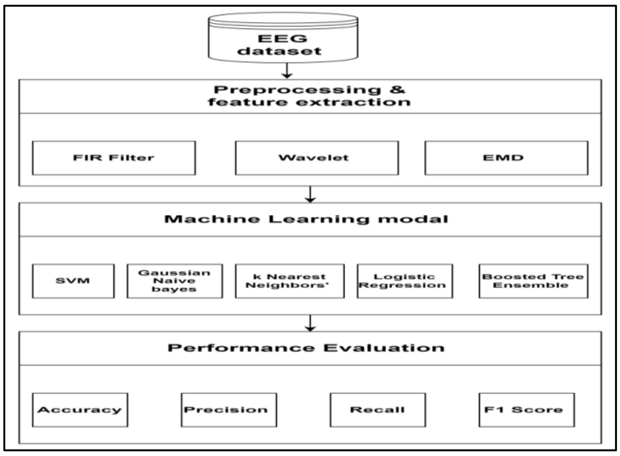

Figure 1 Performance analysis of pre-processing and feature extraction techniques

The present study extracts 43 features from these isolated frequency bands and the original EEG signal. These features include entropy-based measures, maximum power, and energy characteristics within the alpha and beta bands, energy ratios between these ranges, shape factors, and various statistical stress-related characteristics. The gathered 43 features are subsequently inputted into several Machine Learning Classification Algorithms, including Support Vector Machines (SVM), Gaussian Naive Bayes, k-nearest Neighbours (KNN), Logistic Regression, and Boosted Tree Ensembles. Researchers assess the effectiveness of each algorithm using various assessment measures, including accuracy, precision, recall, and F1 score, to identify and categorize distinct mental states and diagnose stress.

4.Comparative analysis of Pre-processing and Feature Extraction techniques

This research study analyses EEG signals associated with stress using the Deap dataset. According to the research article [16-18], the frequency ranges of the alpha band (8–13 Hz) and the beta band (13–30 Hz) are associated with stress. In the context of EEG data analysis, this system employs pre-processing techniques such as finite impulse response filter(FIR filter), wavelet transform, and empirical mode decomposition(EMD).This research uses FIR filters to improve signal quality and extract relevant information, which is crucial for stress detection. This study utilizes band-pass FIR filters to isolate alpha and beta frequency range signals, which are essential for noise reduction and accurate feature extraction, thereby enhancing the accuracy of the stress detection algorithm. Denoising alpha and beta signals from EEG signals through FIR are represented by Figures 2 and 3 as follows.

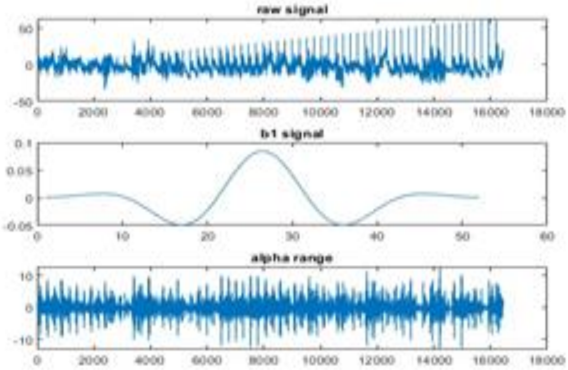

Figure 2 Denoising Alpha signal with FIR

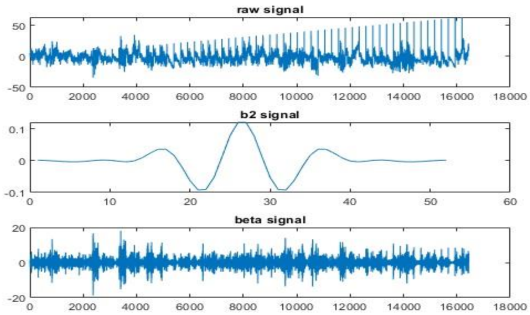

Figure 3 Denoising Beta signal with FIR

Wavelet transform is a versatile tool that is particularly useful for analyzing the complex dynamics of EEG signals, especially in stress identification, because it can capture both temporal and frequency-domain information. Its robustness and computational efficiency also help identify stress in EEG data [19]. Researchers use wavelet transform in many EEG signal processing applications for denoising and feature extraction tasks. The wavelet decomposition algorithm systematically breaks down EEG signals into different frequency components using approximation and detail coefficients at each decomposition level. Researchers can choose from various wavelet families based on data characteristics and analysis objectives. In this study, the db5 wavelet is utilized to decompose EEG signals up to five levels using the wavedec function. Subsequently, signal levels 3 and 4, corresponding to the beta and alpha frequency ranges, are selected for further analysis, as shown in Figure 4.

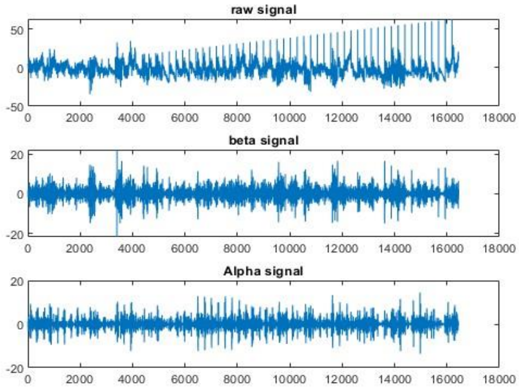

Figure 4 Denoising with Wavelet

EMD is crucial in scientific investigations focused on detecting stress using EEG signals. By decomposing complex, non-stationary EEG signals into IMFs, EMD enables researchers to extract appropriate features for analysis. This technique enhances stress detection accuracy by facilitating targeted feature extraction from specific frequency bands or events of interest[20-22].In this research, EEG signals undergo decomposition into IMFs utilizing the EMD method, extending up to three levels. Following this decomposition, IMFs associated with the beta and alpha frequency ranges are specifically chosen for subsequent analysis, as presented in Figure 5.

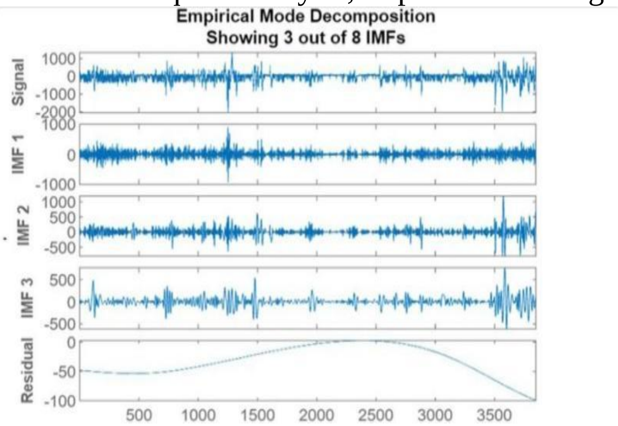

Figure 5 Denoising with EMD

In scientific studies, researchers evaluate pre-processing and feature extraction techniques by considering their capabilities to handle noise and artifacts in EEG data, their performance, and the influence of feature extraction techniques.[23-26]

The mathematical model uses the terms T.P. (true positive), T.N. (true negative), F.P. (false positive), and F.N. (false negative) [27] are discussed in the research article as follows

1.Accuracy measures the proportion of correct predictions to the total predictions, as mentioned in equation (1)

$$\text{Accuracy} = \left(\frac{TP+TN}{FP+FN+TP+TN}\right) *100\ \% \quad (1)$$

2. Precision quantifies the percentage of positive forecasts that come true, as shown in equation (2)

$$\text{Precision} = \left(\frac{TP}{FP+TP}\right) *100\ \% \quad (2)$$

3. Recall measures the number of correct positive predictions out of all actual positive instances, as stated in the equation. (3)

$$\text{Recall} = \left(\frac{TP}{FN+TP}\right) *100\ \% \quad (3)$$

4. The F1 score is a balance of precision and recall, as described in equation (4)

$$\text{F1 score} = \left(\frac{2*\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}}\right) *100\ \% \quad (4)$$

The mathematical formula compares different evaluation parameters for various machine learning algorithms.

Table 1 Performance Evaluation of FIR

Sr No	Algorithm	Accuracy(%)	Precision (%)	Recall(%)	F1score (%)
1	Support Vector Machine	78	75.4	85	79.94

2	Gaussian Naive Bayes	69	70	68	68.98
3	K-Nearest Neighbors	35	50	38.46	43.46
4	Logistic Regression	68	69	67	67.98
5	Boosted Tree Ensemble	50	40	50	44.4

Table 2 Performance Evaluation of Wavelet

Sr No	Algorithm	Accuracy(%)	Precision (%)	Recall(%)	F1score (%)
1	Support Vector Machine	81.7	79.22	87.14	82.99
2	Gaussian Naive Bayes	73	81	73	79
3	K-Nearest Neighbors	60	80	61.53	63.6
4	Logistic Regression	75	70	68	68.9
5	Boosted Tree Ensemble	64	64	64	78

Table 3 Performance Evaluation of EMD

Sr No	Algorithm	Accuracy(%)	Precision (%)	Recall(%)	F1score (%)
1	Support Vector Machine	75	80	72.72	76.18
2	Gaussian Naive Bayes	73	81	73	79

3	K-Nearest Neighbors	67	69	67.72	68.3
4	Logistic Regression	65	80	61.53	63.63
5	Boosted Tree Ensemble	60	90	56.25	69.23

Three pre-processing and feature extraction methods are evaluated based on the accuracy, precision, recall, and F1 score of stress detection to facilitate the diagnosis of stress and the classification of various mental states. A comparative analysis of the precision scores of several machine learning algorithms is shown in Tables 1,2, and 3 when applied to varied signal processing techniques, namely, FIR, Wavelet, and EMD.

The Wavelet technique consistently demonstrated the highest precision scores across most algorithms, indicating its effectiveness in extracting pertinent features for classification. SVM achieved commendable results in conjunction with the Wavelet technique.

4.Discussion

Discussion

In stress detection research, where datasets are complex and feature-rich, optimizing feature selection is essential for improving the machine learning model's effectiveness and reliability. By carefully selecting relevant features, the genetic algorithm (G.A.) efficiently reduces dataset dimensionality, addressing computational challenges and mitigating overfitting risks. This approach enhances model generalization while optimizing performance, leading to the development of more efficient stress detection models.[28]

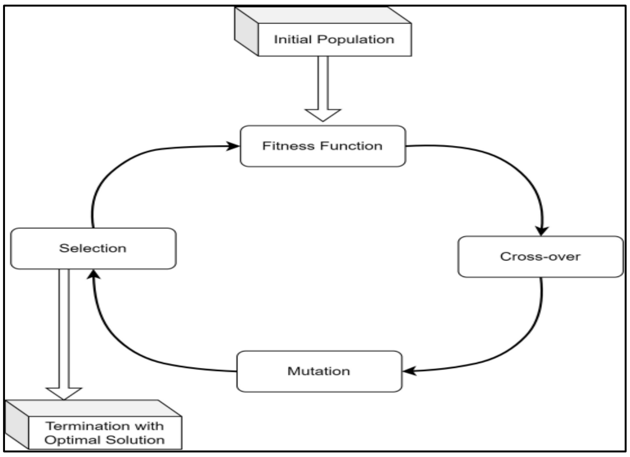

Figure 6 Genetic Algorithm workflow

G.A. offers a powerful approach for optimizing feature selection in EEG signal analysis inspired by natural selection principles, as shown in Figure 6. G.A. identifies subsets that effectively distinguish emotional stress states by systematically exploring the vast feature space. Through iterative processes resembling natural selection, including selection, crossover, and mutation, G.A. refines feature subsets to achieve higher fitness scores for improved stress detection. This methodology facilitates accurate real-time classification of EEG signal stress levels, enhancing its suitability in research contexts. This approach enables precise real-time stress level classification in EEG signals, enhancing its applicability in research settings.

5. Wavelet-G.A. Fusion-based Enhanced Mental Stress Detection via EEG

Wavelet-GA Fusion-based Enhanced Mental Stress Detection via EEG

The proposed system aims to identify the most informative and relevant features from a dataset while reducing redundancy and noise. This method enhances model performance and reduces computational complexity. Researchers effectively use the G.A. as a powerful technique for optimized feature selection.

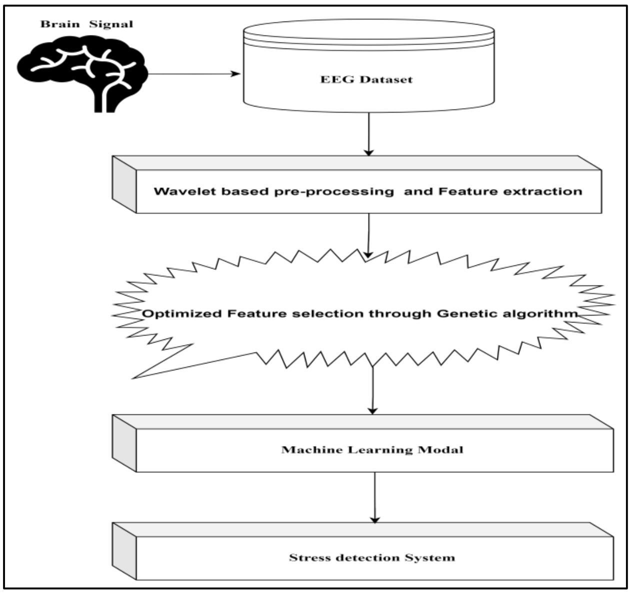

Figure 7 The Proposed to Enhanced Mental Stress Detection Using EEG

In this research study, EEG signals emerge as a vital tool for capturing the brain's electrical activity, offering valuable insights into cognitive functions and emotional responses. Through an extensive comparative analysis of feature extraction and pre-processing techniques applied to EEG signals, the study underscores the superior performance of wavelet methodology on an online EEG dataset compared to FIR filtering and EMD techniques. This study extracts 43 features from the EEG signals, subsequently feeding them into various Machine Learning Classification Algorithms utilizing the wavelet approach. Notably, the results demonstrate a remarkable accuracy of 81.7%, a precision of 79.22%, a recall of 87.14%, and an F1 score of 82.99%. This proposed system implements the G.A. for feature selection from EEG signals to optimize stress detection systems to extract meaningful information directly. This method involves initializing the algorithm with parameters such as a population size of 20, utilizing 43 features, running for 100 generations, and employing a mutation rate of 0.01. The GA main loop encompasses fitness evaluation, parent selection, crossover, mutation, and population replacement. Ultimately, the top five features identified after the optimization process by the G.A. include Shape factor (Raw Signal), power of beta, RMS (alpha), Skewness (beta), and Energy of beta. These findings contribute significantly to the advancement of EEG-based stress detection systems and underscore the effectiveness of employing G.A. for feature selection in neuroscience research.

Table 4 Performance Evaluation of the proposed Enhanced mental stress detection using EEG

Sr No	Algorithm	Accuracy(%)	Precision (%)	Recall(%)	F1score (%)
1	Support Vector Machine	87	78	93	84.8
2	Gaussian Naive Bayes	85	77	88	82.1
3	K-	69	88	63.	73.9

	Nearest Neighbors			8	
4	Logistic Regression	80	76	86	80.69
5	Boosted Tree Ensemble	69	70	68	68.98

This study introduces a novel approach for mental stress detection via EEG signals, employing wavelet technology integrated with a refined feature selection optimization algorithm, G.A., and applying the SVM algorithm for classification. Experimental results, as demonstrated in Table 4, reveal a notable accuracy of 87%. The system effectively detects mental stress with high precision by integrating wavelet analysis for EEG signal processing, G.A. for feature selection, and SVM for classification. This integrated approach showcases the potential of combining cutting-edge technologies for accurate and reliable mental stress detection using EEG signals.

6. Hardware Implementation

After physician consultation, as shown in Figure 8, this research considers only the raw signal's alpha and beta range values to determine stress. Researchers use the top five optimized features identified by the G.A. to train and test the dataset for stress classification and identify whether the person is stressed or not. After classification, the SVM classifier gives the comparative best output. Therefore, researchers further utilize it. They export the trained model of SVM and deploy this code on the Raspberry Pi hardware [29].

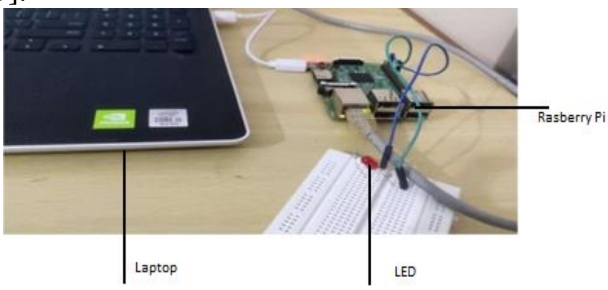

Figure 8. Hardware implementation of stress detection system

According to the mental condition, researchers make the LED blink if a person is 'stressed' and turn it off if the person is 'normal.' They display the final output using an LED.

Conclusion

This study presents a comprehensive EEG-based mental stress detection analysis, highlighting the critical role of pre-processing and feature extraction techniques in improving accuracy and reliability. Through a systematic comparative analysis, researchers find that wavelet methodology is the most effective approach, displaying superior performance in extracting pertinent features for stress classification. Furthermore, they integrate G.A. for optimized feature selection to enhance model performance. The successful implementation of the proposed approach on hardware, specifically Raspberry Pi, underscores its utility and applicability in real-world scenarios. This integration yields a robust stress detection system that accurately identifies stress levels in individuals, as demonstrated by the LED-based output. Thus, this research provides valuable insights and methodologies for developing efficient and reliable EEG-based stress detection systems, with potential implications across various disciplines, including healthcare and neuroscience.

Conflicts of interest/Competing interests: (include appropriate disclosures)

The authors declare no conflict of interest.

Authors' contributions:
Sangita Patil experimented with detecting mental stress via EEG, comparing different pre-processing and feature extraction methods such as finite impulse response filters, wavelet transforms, and empirical mode decomposition. To enhance model performance, she integrated optimized feature selection with genetic algorithms. Dr. Ajay Paithane verified the experiment, boosting its credibility.

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