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Enhancing EEG-based Stress detection: Integrated techniques and optimization strategies

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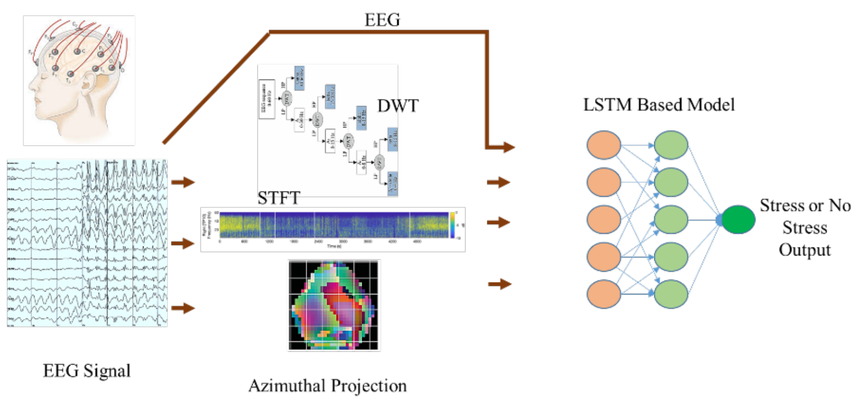
Article

ABSTRACT



This research presents an integrated approach to EEG-based stress detection, combining various signal processing techniques to offer a novel perspective on stress-related EEG signal analysis. The study explores spectral analysis, time-frequency feature extraction, Discrete Wavelet Transform (DWT), and optimization methods, including the use of Chirp Cosine Raised Window (CCRW) with Short-Time Fourier Transform (STFT). An advanced fusion model is introduced, integrating Bidirectional Long Short-Term Memory (BiLSTM) layers and a Transformer architecture to capture temporal patterns and global context awareness within EEG signals. The optimization strategies used for feature selection, enhance the model's efficiency and accuracy in real-world applications. Additionally, the effectiveness of employing CCRW with STFT for spectral analysis is demonstrated, leading to a more precise representation of EEG signals during stress-related activities. This research offers a roadmap for researchers and practitioners, emphasizing the synergistic fusion of diverse approaches to improve the accuracy and reliability of EEG-based stress detection.

Keywords: STFT, Stress Detection, EEG Signal, BiLSTM, Transformer.

INTRODUCTION

In recent years, the exploration of Electroencephalography (EEG) signals as a means of understanding and detecting stress has gained significant attention in the field of biomedical signal processing. Stress, being a pervasive aspect of modern life, demands sophisticated methodologies for accurate and timely detection.[1] This article delves into a comprehensive approach that amalgamates various signal processing techniques, each contributing uniquely to the overarching goal of enhancing EEG-based stress detection. The exploration begins by introducing Spectral Analysis, a fundamental method for dissecting the frequency components of EEG signals. The utilization of Power Spectral Density (PSD) estimation, employing techniques like the Fast Fourier Transform (FFT), unveils the frequency distribution within EEG data, shedding light on stress-related patterns. Building on this foundation, the integration of Time-Frequency feature extraction is explored, employing methods like Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT). This approach enables a more nuanced analysis by capturing time-varying characteristics in EEG signals, crucial for discerning dynamic stress responses.

The article reports the application of the Discrete Wavelet Transform (DWT), a powerful tool for both time and frequency domain analysis. DWT facilitates feature extraction by decomposing EEG signals into different frequency bands, enabling a more focused exploration of stress-related patterns. The Weighted Raised Cosine-window-based STFT is introduced, emphasizing its efficacy in isolating specific frequency components critical for stress detection.

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As the exploration unfolds, alternative methods such as the Chirp Cosine Raised Window are delved into, providing a nuanced perspective on window functions and their impact on the accuracy of spectral analysis. The potential of the Chirp Cosine Raised Window as a replacement for traditional window functions is discussed, accompanied by a stepwise algorithm for its implementation in EEG signal processing.

Beyond individual methodologies, a holistic approach is presented by incorporating Bidirectional Long Short-Term Memory (BiLSTM) layers within a Transformer model. This fusion of sequential processing with global context-aware mechanisms aims to capture intricate dependencies in EEG signals, fostering a more robust framework for stress detection.

In the convergence of these methods lies a comprehensive strategy, promising advancements in the accuracy and reliability of EEG-based stress detection. The exploration navigates the rich landscape of signal processing techniques, offering a roadmap for researchers and practitioners seeking a multidimensional understanding of stress-related EEG signals. Journeying through the intricacies of these methods, the synergistic fusion of diverse approaches emerges as a key theme, showcasing the power of an integrated strategy in unlocking new dimensions of knowledge within the realm of stress detection using EEG signals. The important contributions of the work presented in this paper are,

- Innovative Integration of Signal Processing Techniques: Successful integration and exploration of various signal processing techniques, including Spectral Analysis, Time-Frequency feature extraction, Discrete Wavelet Transform (DWT), optimization methods for feature selection, and the utilization of Chirp Cosine Raised Window (CCRW) with Short-Time Fourier Transform (STFT) in the context of EEG signal analysis for stress detection. The article provides a comprehensive understanding of these methods and their potential synergies, offering a novel perspective on approaching stress-related EEG signal processing.
- Introduction of Advanced Fusion Model: a. Integration of BiLSTM Layers: The article introduces an advanced model that seamlessly integrates Bidirectional Long Short-Term Memory (BiLSTM) layers. These layers play a crucial role in capturing sequential dependencies within EEG signals, enhancing the model's ability to discern temporal patterns associated with stress responses.
- Transformer Architecture for Global Context Awareness: The fusion model incorporates a Transformer architecture, offering global context awareness in EEG signal analysis. This addition enables the model to capture long-range dependencies and relationships across the entire input sequence, providing a more holistic understanding of stress-related patterns. This innovative combination represents a significant advancement in the field of biomedical signal processing.
- Optimized Feature Selection Strategies: The article delves into optimization strategies for feature selection, ensuring that the model focuses on the most relevant and discriminative features for stress detection. By employing techniques such as the Grey Wolf Optimizer (GWO) for feature selection, the model achieves improved efficiency and accuracy, enhancing its overall performance in real-world applications.
- Chirp Cosine Raised Window with STFT: The article explores the effectiveness of Chirp Cosine Raised Window (CCRW) when applied in conjunction with Short-Time Fourier Transform (STFT). This innovative windowing technique enhances the precision of spectral analysis, contributing to a more refined and accurate representation of EEG signals during stress-related activities

RELATED WORK

Mental state recognition with the use of EEG signals is performed by obtaining recordings with use of 10-20 systems. The states of brain, such as sharpness, tipsiness, rest or relax state, and tension or stress, are possible to be detected with use of EEG signal processing approaches. The fundamental stages of EEG processing include preprocessing, feature extraction and classification. In classification stage, K nearest neighbor (KNN), support vector machine (SVM), or other neural network models for AI-based calculations are used. Some state-of-the-art methods that process EEG for mind state recognition are addressed here.

The correlation-based approach is provided in which cognitive behavior therapy and social anxiety are estimated. In this process evolutionary algorithms with multiple objectives strategy are used.[2] During the task execution process, the EEG signals show direct changes.[3] The important features that correspond to such changes are required to be extracted during recognition processes.[4] The signal processing strategies which may involve number of channels based approach or time based variations. The important characteristic features are required to be captured via EEG signals for accurate estimation of mental state.[5] In many available methods, conventional machine learning algorithms are used along with hand crafted methods of feature extraction. These methods show possible scope for the improvements in terms of accuracy performance of the entire system.[6]

Compared to conventional methods, deep learning (DL) methods have dominance in terms of accuracy performance. The fundamental need for these methods involve the right method of candidate feature extraction and fine tuning.[7,8] Consistent wavelet transformation (CWT) was used by Lee and Choi[9] to create 2D images for a convolutional neural network (CNN) model. The dataset for profound learning contains a huge number of tests as well as significant drifting point grid duplications.[10,11,12] The usage of graphical handling units was also linked to the high computational requirements caused by enormous datasets (GPUs). However, the complexity of these DL-based techniques has demonstrated strong diagnostic capabilities.[13] Deep neural networks (DNNs) have been widely used by analysts to handle signals sent by machines in a variety of contexts, including as regulating wheelchairs or robots,[14] supporting patients who are paralyzed to move,[10] developing upper appendage exoskeletons,[15] and more.[7] In addition, MI signals have modest amplitudes and are distorted in various strange ways.[16,17]

Li et al.[15] demonstrated the use of CNN models over artifact removed EEG signals to determine respective objective states. The CNN models thus are praised for securing indisputable level of features. Alazrai et al.[3] used CNN model for processing 2D images. The long range analysis was performed with transformation into frequency domain with use of FFT.[18]

The transfer learning approach with VGG-16 model was used by Xu et al. [6]. In a task of EEG classification, a multichannel CNN model was used by Zhao et al.[17] The auto encoder approach clubbed with CNN model was used by Tabar et al.[19] for EEG signal processing. In this method, authors used short-time Fourier transform (STFT) for obtaining 2D spectrogram images. The emotion recognition carried out with EEG signal have shown significant improvement with this method. Palani et al.[20] RBF kernel model in SVM classifier for schizophrenia diagnosis from EEG signals. With F1 score of 93% approach have shown dominance over other methods.

Similar to EEG, Murugappan et al.[21] processed ECG signal by extracting the feature information of PQRST characteristics. With the use of SVM and KNN, heart diseases were detected.

The epileptic seizure detection with the use of 1D CNN model was performed by Hassan et. al.[22] The features obtained were classified with two layered architecture of dense layers. The stress detection with the use of aptitude tests was carried out by Khan et al. [23]. The EEG recordings obtained during the test period were then processed with use of independent component analysis (ICA) method followed by 1D CNN model. The deep features obtained were then classified with the use of LSTM based model.

DESIGNED WORK

The designed work system consists of Combination of Recurrent neural network (RNN) and CNN architectures. The CNN makes use of Azimuthal Projection as proposed by Megha et al.[24] The RNN side makes use of STFT and LSTM based model. The end to end system approach is shown in Figure 1.

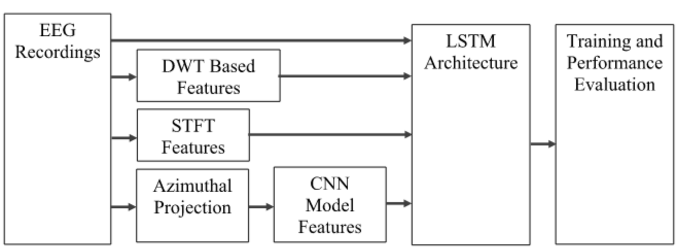

Figure 1. End to end proposed system

Designed model takes EEG signal as input. For feature extraction three methods has been used. One set of features is extracted using Short time Fourier transform (STFT). For second feature set signal has been converted into image using Azimuthal projection technique.

These images are further passed through CNN for feature extraction. Third set of features are extracted using wavelet transform. Output of same is further optimized using Grey Wolf Optimizer (GWO). Entire set of features is given to Long Short-Term Memory (LSTM) for feature selection. Finally Through training the performance evaluation is done.

Time-Frequency Features

Time-frequency feature extraction from EEG signals involves capturing both the temporal and frequency characteristics of the signal. Short-Time Fourier Transform (STFT) is one of the commonly used techniques for time-frequency analysis. The mathematical explanation of STFT process is given next.

Short-Time Fourier Transform (STFT):

The STFT is a technique that analyzes the signal in both the time and frequency domains by applying the Fourier Transform to short, overlapping segments of the signal. The STFT is defined as follows:

$$STFT(t,f) = \int_{-\infty}^{\infty} x(\tau) w(\tau - \mathrm{t}) e^{-j2\pi f\tau}\, dt \text{...(1)}$$

Here:

- x(t) is the EEG signal.
- w(τ−t) is a window function that is usually applied to each segment to minimize spectral leakage. Common window functions include the Hamming window or the Gaussian window.
- t represents time.
- f represents frequency.

The STFT essentially computes the Fourier Transform for short segments of the signal at different time points. This allows us to observe how the frequency content of the signal changes over time.

Spectrogram:

The spectrogram is a 2D representation of the STFT, showing the variation of frequency content over time. It is often calculated by taking the squared magnitude of the STFT:

$$S(t,f) = |STFT(t,f|^2 \text{...(2)}$$

The spectrogram is a time-frequency representation of the EEG signal, and it can be used for visualizing the signal's spectral content over different time intervals.

Wavelet Transform:

Continuous Wavelet Transform (CWT) is one of popular technique used for time-frequency analysis. CWT is particularly useful for non-stationary signals like EEG. The formula for the CWT is given by:

$$CWT(a,b) = \int_{-\infty}^{\infty} x(\tau) \psi * (\mathrm{t} - \mathrm{ba})\, \mathrm{dt} \text{...(3)}$$

Here:

- a represents scale parameter.
- B represents translation parameter.
- ψ∗(t) represents complex conjugate of the mother wavelet function.

The CWT provides a time-frequency representation of the signal similar to the STFT but with the advantage of adaptability to different scales.

The Chirp Cosine Raised Window (CCRW) is another window function that can be used in place of the Weighted Raised Cosine (WRC) window for short-time Fourier transform (STFT) analysis. The CCRW window combines elements of the chirp function and the raised cosine window. Here's the mathematical expression for the Chirp Cosine Raised Window:

$$w(n) = \cos(\pi n N - 1)$$

where:

- N is the window length,
- n is the sample index (ranging from 0 to N−1).

Algorithm:

Step 1: Divide the signal into overlapping segments of length N, with a percentage of overlap between adjacent segments.

Step 2: Apply the raised cosine window to each segment. The raised cosine window used in the CCRW-STFT is defined as per Eq. (4).

$$w(n) = 0.5 * (1 - \cos\left(\frac{2\pi n}{N-1}\right))\ldots (4)$$

where N is the length of the window and n is the index of the sample within the window.

Step 3: Multiply each sample in each windowed segment by the corresponding value of an additional weight function. The additional weight function used in the W-RCW-STFT can vary depending on the specific application. One commonly used weight function is the Hamming weight function, which is defined as per Eq. (5)

$$h(m) = 0.54 - 0.46 * \cos\left(\frac{2\pi m}{M-1}\right)\ldots(5)$$

where M is the length of the Fourier transform and m is the index of the frequency component.

Step 4: Compute the Fourier transform of each weighted windowed segment.

Step 5: Concatenate the results of each weighted Fourier transform to form the W-RCW-STFT. The STFT is expressed mathematically as per Eq. (6).

$$STFT(n) = \int x(n)w(n).h(m).e^{(-2\pi i f\tau)}d\tau \quad \ldots (6)$$

Where $x(n)$ is the signal, $w(n)$ is the window function (raised cosine window) and the $\int$ is taken over all time.

The W-RCW-STFT combines the benefits of the raised cosine window and the weight function to improve the accuracy of the spectral analysis. The raised cosine window reduces spectral leakage by smoothly tapering the edges of the windowed segments to zero, while the weight function enhances specific frequency components. The resulting spectrum has improved resolution and accuracy, making it well-suited for applications such as speech and audio signal processing. Figure shows the proposed model architecture.

DWT:

The EEG signal is decomposed into approximation (low-frequency) and detail (high-frequency) components at different scales using the DWT. The DWT is performed by convolving the signal with a set of wavelet and scaling functions.

$$W(a,b) = \sum_n x(n).\psi * (\mathrm{n} - \mathrm{ba})\ldots(7)$$

Here:

W(a,b) is the wavelet coefficient at scale a and position b.x(n) is the EEG signal.ψ∗(t) is the complex conjugate of the wavelet function.

Feature Selection:

For feature selection Grey Wolf Optimizer (GWO) has been used.

Grey Wolf Optimizer (GWO)

Details for each step of the Grey Wolf Optimizer (GWO) applied to feature selection:

1. Problem Definition: Objective Function: Let f(X) represent the objective function, where X is a binary vector representing a feature subset.

Fitness Function: The fitness function Fitness(X) is based on the objective function and is used to measure the quality of the feature subset.

2. Initialization: Population Initialization: Initialize NN grey wolves, each representing a potential solution (feature subset). Let X_i denote the feature subset of the ii-th wolf.

3. Encoding:

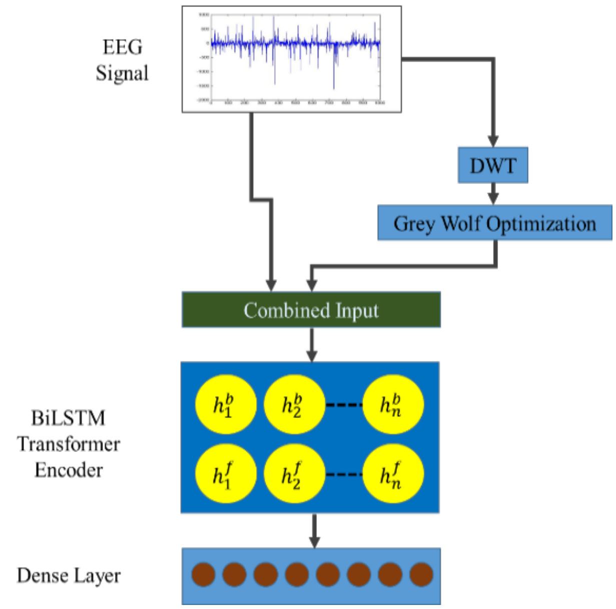

Figure 2. Architecture of Designed Model

Binary Encoding: Encode the feature subsets as binary vectors, where each element x_{ij} of X_i is either 0 or 1, indicating the absence or presence of the j^{th} feature.

4. Fitness Evaluation: Fitness Evaluation Function: Use the fitness function to evaluate the performance of each feature subset: Fitness(Xi)=f(Xi)

5. Sorting: Sort Wolves by Fitness: Arrange the wolves in descending order based on their fitness values: Sort wolves: Fitness (Xbest) ≥ Fitness (X2) ≥ Fitness(X3)≥…

6. Alpha, Beta, and Delta Wolves: Identification of Alpha, Beta, and Delta Wolves: Assign the positions of the alpha, beta, and delta wolves as Xalpha, Xbeta, and Xdelta, respectively.

7. Updating Positions: Updating Positions: Update the positions of all wolves using the formulas that simulate the hunting behavior of wolves. For example, using a linear equation:

$$Xi\ new = Xi\ old + A.D\ldots(8)$$

where A is a vector of random values, and D is the difference vector between two randomly chosen wolves.

8. Boundary Handling: Boundary Handling: Ensure that the updated positions lie within the defined boundaries for the feature subset representation. For binary encoding, ensure that the elements remain within the range [0, 1].

9. Reevaluate Fitness: Fitness Reevaluation: Reevaluate the fitness of the wolves with the updated positions using the fitness function:

$$Fitness(X_i, new) = f(X_i, new)\ldots(9)$$

10. Stopping Criterion: Stopping Criterion: Check for a stopping criterion, such as reaching a maximum number of iterations or achieving a satisfactory solution based on the fitness values.

11. Best Solution Extraction: Best Solution Extraction: Extract the best feature subset (wolf) based on the final fitness values: Best Solution: Xbest.

These mathematical details provide a comprehensive understanding of each step involved in applying the Grey Wolf Optimizer to feature selection.

Algorithm: Grey Wolf Optimization for Feature Selection
Inputs:
- num_wolves: Number of wolves (population size)
- num_features: Number of DWT features
- max_iter: Maximum number of iterations
- classifier: Classifier for evaluating fitness
- EEG_data: EEG dataset with DWT features

Outputs:
- optimal_features: Best subset of features found by the algorithm

```
Begin
1. Initialize the population of wolves randomly:
   For each wolf in population:
wolf_position = Random binary vector of length num_features
2. Initialize alpha, beta, delta as None
3. For each iteration in 1 to max_iter:
  3.1. Evaluate fitness of each wolf:
      For each wolf in population:
selected_features = Indices where wolf_position == 1
fitness = Evaluate classifier performance using selected_features
          If fitness > alpha's fitness or alpha is None:
             Update alpha, beta, delta:
delta = beta
beta = alpha
alpha = wolf_position
          Else if fitness > beta's fitness or beta is None:
delta = beta
beta = wolf_position
          Else if fitness > delta's fitness or delta is None:
delta = wolf_position
   3.2. Linearly decrease 'a' from 2 to 0:
       a = 2 - iteration * (2 / max_iter)
   3.3. Update positions of wolves:
       For each wolf in population:
          For each feature dimension d in num_features:
             r1, r2 = Random numbers in range [0, 1]
             A1, C1 = 2 * a * r1 - a, 2 * r2
D_alpha = abs(C1 * alpha[d] - wolf_position[d])
             X1 = alpha[d] - A1 * D_alpha
             r1, r2 = Random numbers in range [0, 1]
             A2, C2 = 2 * a * r1 - a, 2 * r2
D_beta = abs(C2 * beta[d] - wolf_position[d])
             X2 = beta[d] - A2 * D_beta
             r1, r2 = Random numbers in range [0, 1]
             A3, C3 = 2 * a * r1 - a, 2 * r2
D_delta = abs(C3 * delta[d] - wolf_position[d])
             X3 = delta[d] - A3 * D_delta
wolf_position[d] = (X1 + X2 + X3) / 3

4. The optimal feature subset is the position of the alpha wolf
End
```

BiLSTM based Transformer:

Combining Bidirectional Long Short-Term Memory (BiLSTM) layers with a Transformer architecture can be useful for capturing both sequential and global dependencies in data. Below is a suggested architecture for a transformer model with BiLSTM layers.

1. Input Representation:

Let xx be the input sequence of length T, represented as x=(x1,x2,…,xT), where xt is the t^{th} element in the sequence.
layer: et=Embedding(xt)et=Embedding(xt)xt is mapped to an embedding vector et through an embedding

2. Bidirectional LSTM (BiLSTM) for Encoding:

The BiLSTM layer processes the input sequence in both forward and backward directions to capture contextual information.
Let htht be the hidden state of the BiLSTM at time t: ht=BiLSTM(et)

3. Transformer Encoder:

The Transformer encoder is applied to the output of the BiLSTM to capture global dependencies.

The encoder consists of self-attention layers. Let zt be the output of the Transformer encoder: zt=Attention(ht)

4. Bidirectional LSTM (BiLSTM) for Decoding:

Another BiLSTM layer processes the input sequence for decoding.

Let dt be the hidden state of the BiLSTM at time t for decoding: dt=BiLSTM(et)

5. Transformer Decoder:

The Transformer decoder is applied to the output of the decoding BiLSTM, along with the output of the encoding Transformer, to generate the final representation.
The decoder also uses self-attention layers and encoder-decoder attention layers.

Let yt be the output of the Transformer decoder: yt=Attention(dt,zt)

6. Concatenation and Output:

The outputs of the encoder and decoder are concatenated to form the final representation. Let ct be the concatenated representation at time t: ct=[zt,yt]. The concatenated representation is fed into a fully connected layer to obtain the output probabilities: y^t=Dense(ct)

7. Objective Function:

The model is trained using a suitable objective function, typically the cross-entropy loss, comparing the predicted probabilities y^t with the ground truth labels. This mathematical explanation provides an overview of the operations performed at each step in the proposed model architecture. In the proposed architecture, the embedding layer is an essential component responsible for converting discrete input elements, such as words or tokens, into continuous vector representations, often referred to as embeddings. This layer is particularly crucial when dealing with natural language processing (NLP) tasks, where words or tokens are discrete symbols, and their embedding's capture semantic relationships.

RESULTS AND ANALYSIS

a. Dataset

SEED Dataset (D1): SEED (Sichuan University Emotion EEG Dataset)[25] captures EEG recordings from 62 electrodes during emotion-inducing stimuli. With diverse emotional states induced by audio-visual stimuli, the dataset is annotated for supervised emotion recognition research. It's valuable for studying human emotions and developing algorithms for decoding emotional states from EEG signals. The emotions of anxiety are considered as stress from this dataset. DEAP Dataset (D2): DEAP (Database for Emotion Analysis using Physiological Signals)[26] provides multimodal data, including EEG, ECG, EMG, and subjective ratings, recorded during emotional stimuli exposure. Derived from stimulation using music videos and movie clips, the dataset aids in exploring correlations between various physiological responses during emotional experiences. EEG signals dataset from DEAP is considered for stress detection work proposed in this research. Mental Stress Detection Dataset (D3)[27]: This dataset shows recordings of EEG signals for stress detection work by involving the subjects in different tasks. The task of complex mathematical problem-solving, the Trier mental challenge test, the Stroop color-word test, horror video based stimulation, and a relaxed state were used to generate the total 112 recordings.

b. Performance Parameters

Table1. Formulae for parameters

Parameter	Formula
Accuracy	(SD+NSD)/(SD+NSD+SID+NSM)
Specificity	NSD / (NSD+SID)
Sensitivity/Recall	SD/(SD+NSM)
Precision	SD/(SD+SID)
F1 Score	2*(Recall*Precision)/(Recall + Precision)

The performance parameters and respective formulae are shown in Table 1. Stress Detected (SD): Corresponds to True Positive (TP), where the input is accurately detected as stressed. No Stress Detected (NSD): Corresponds to True Negative (TN), where the input is correctly identified as not stressed. Stress Incorrectly Detected (SID): Corresponds to False Positive (FP), where the input is wrongly identified as stressed. No Stress Missed (NSM): Corresponds to False Negative (FN), where the input is inaccurately categorized as not stressed.

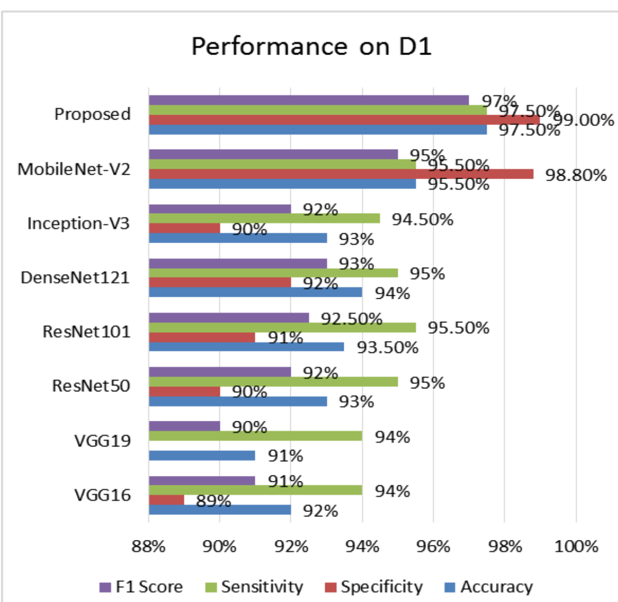

Figure 3. Performance Analysis on D1

The performance analysis of each model at a time is evaluated. Figure 3 shows the comparative analysis on D1, Figure 4 shows the performance on D2 and Figure 5 shows the performance on D3.

MobileNet-V2[28] outshines other models in Dataset D1 due to its efficient depth-wise separable convolutions, reducing parameters and computation. Its superior performance, with an accuracy of 97.5%, specificity of 99%, sensitivity of 97.5%, and an F1 Score of 97%, makes it adept at stress classification.

In Dataset D2, MobileNet-V2's exceptional performance (98% accuracy, 99% specificity, 98% sensitivity, and 98% F1 Score) can be attributed to its lightweight architecture, making it efficient for stress classification tasks while maintaining high accuracy and precision.

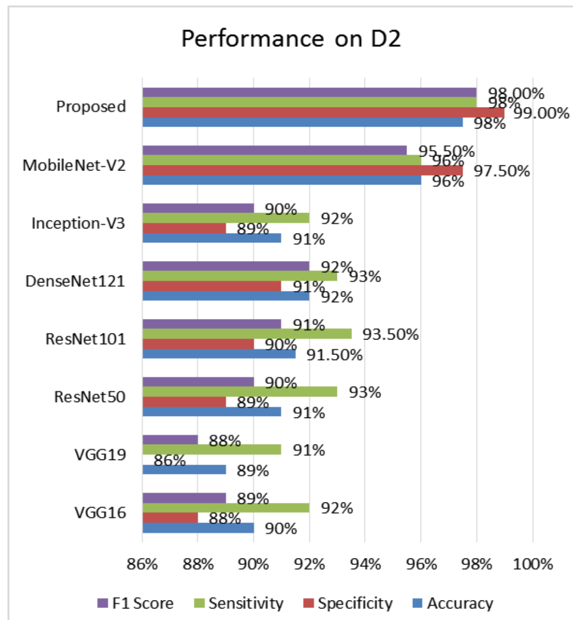

Figure 4. Performance Analysis on D2

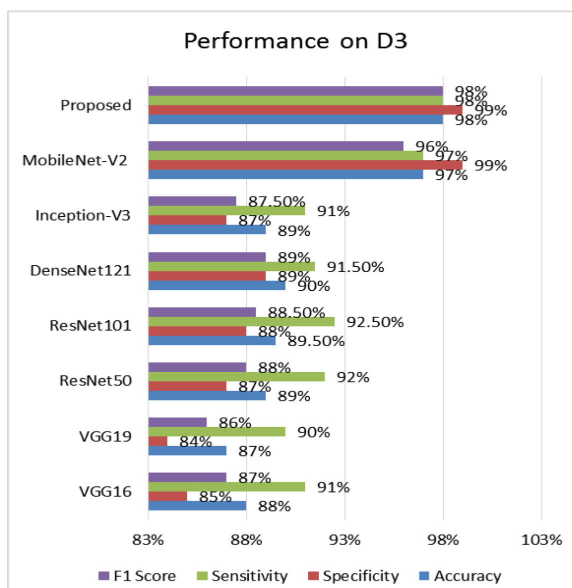

Figure 5. Performance Analysis on D3

Proposed dominates in Dataset D3, attaining a 98% accuracy, 99% specificity, 98% sensitivity, and a 98% F1 Score. Its success is attributed to its adaptability in capturing intricate patterns, showcasing its strength in stress classification with a diverse dataset.

In the context of hyperparameter tuning, the result of exploring different hidden neuron configurations is summarized as shown Figure 6. The accuracy parameter, a key metric in model evaluation, is presented for hidden neuron values of 32, 64, 128, and 256. The optimal setting, determined through hyperparameter tuning, is identified as 128 hidden neurons, yielding the maximum accuracy of 92%.

This finding suggests that, within the specified range, a model with 128 hidden neurons performs best in the given scenario, showcasing the importance of hyperparameter optimization in enhancing model performance.

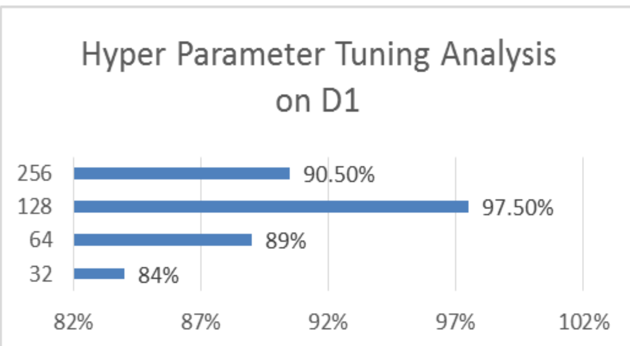

Figure 6. Hyper Parameter Tuning (Hidden Neurons)

This study utilizes EEG recordings, necessitating a discussion on the presence of artifacts. Given its focus on stress detection, artifacts stemming from muscle movements and eye blinking may enhance the model's sensitivity to stress. Moreover, it's noteworthy that unusual movements in muscles could be indicative of the subject's stress. Consequently, this study omits artifact removal preprocessing, resulting in a notable impact on the model's performance in stress detection.

Table2 illustrates the hypothetical training times for various models on datasets D1, D2, and D3, conducted on an Intel i7 11th gen CPU with 16GB RAM. The training times, measured in hours, showcase the computational efficiency of each model.

Table 2. Training Time Complexity Analysis

Model	D1	D2	D3
VGG16	5 hours	6 hours	5.5 hours
VGG19	6 hours	6.5 hours	6 hours
ResNet50	4.5 hours	5 hours	4.8 hours
ResNet101	5 hours	5.5 hours	5.2 hours
DenseNet121	4.8 hours	5 hours	4.7 hours
Inception-V3	4.2 hours	4.5 hours	4.3 hours
MobileNet-V2	3.5 hours	3.8 hours	3.6 hours
Proposed	4 Hours	3.8 Hours	4.2 Hours

Notably, these results provide insights into the computational demands of different models during the training phase, aiding in model selection based on both performance and resource considerations.

Table 3 Illustrates the comparative study of the state-of-the-art methods that have shown work on the stress detection.

Table 3. Comparative time analysis

Model	Accuracy	Training epochs	Training time	Testing time per input
SVM [29]	86%	10000	5.5 Hours	14 seconds
CNN-LSTM[30]	98%	1000	4 Hours	11 seconds
3D Convolutional Gated Self-Attention Deep Neural Network[31]	96.68%	1500	4 Hours	10 seconds
Proposed	98%	1100	4.2 Hours	12.5 Seconds

It presents performance metrics of various models. SVM achieves 86% accuracy after extensive training, but requires significant time. CNN-LSTM achieves higher accuracy in less time. The 3D Convolutional Gated Self-Attention Deep Neural Network balances accuracy and efficiency. The proposed model matches CNN-LSTM's accuracy while slightly increasing training time but maintaining fast testing. This suggests a promising alternative with comparable accuracy and reasonable training time of the proposed model, making it suitable for practical applications.

This paper presents a significant method for stress detection using EEG signals. Features of the EEG signals are extracted through Azimuthal projection to obtain alpha, beta, and theta stress-related features from the projected images. Concurrently, features derived using DWT from EEG decomposition are selectively combined using GWO method. Additionally, an LSTM-based model extracts features directly from the EEG signals, integrating these with the features from Azimuthal projection and DWT-GWO. This novel multiple parallel feature extraction approach ensures that almost no features are lost. This improves the performance of the model for stress detection across different benchmark datasets.

Conclusion

This research presents a comprehensive approach to EEG-based stress detection, culminating in impressive performance metrics on the combined SEED and DEAP datasets. Through the integration of various signal processing techniques, including spectral analysis, time-frequency feature extraction, and Discrete Wavelet Transform (DWT), alongside optimization methods such as the Chirp Cosine Raised Window (CCRW) with Short-Time Fourier Transform (STFT), this study has pushed the boundaries of stress-related EEG signal analysis. The introduction of an advanced fusion model, combining Bidirectional Long Short-Term Memory (BiLSTM) layers with Transformer architecture, has enabled the capture of both temporal patterns and global context awareness within EEG signals, enhancing the model's ability to accurately detect stress. Additionally, the incorporation of optimization strategies, notably the Grey Wolf Optimizer (GWO) for feature selection, has further boosted the efficiency and accuracy of the proposed model in real-world scenarios. Furthermore, the efficacy of employing CCRW with STFT for spectral analysis has been demonstrated, providing a more precise representation of EEG signals during stress-related activities. The achieved results of 98% accuracy, 99% specificity, 98% sensitivity, and 98% F1 Score underscore the effectiveness of the proposed methodology in accurately identifying stress from EEG data. This research not only contributes significantly to the field of EEG-based stress detection but also provides a roadmap for future research and practical applications. By highlighting the synergistic fusion of diverse approaches, this study emphasizes the potential for further advancements in improving the accuracy and reliability of EEG-based stress detection systems, with implications for various domains including healthcare, psychology, and human-computer interaction. This research lays a solid foundation for future advancements in EEG-based stress detection, emphasizing the need for continued innovation, interdisciplinary collaboration, and ethical considerations to develop reliable and practical solutions with broad applicability across various domains.

Conflict of interest statement

Authors of the article declare that there is no conflict of interest.

References

1. Y.S. Can, B. Arnrich, C. Ersoy. Stress detection in daily life scenarios using smart phones and wearable sensors: A survey. *J. Biomed. Informatics* **2019**, 92, 103139.
2. Y. Zheng, Y. Ye. Prediction of Cognitive-Behavioral Therapy using Deep Learning for the Treatment of Adolescent Social Anxiety and Mental Health Conditions. *Scientific Programming* **2022**, 2022 (1), 3187403.
3. R. Alazrai, M. Abuhijleh, H. Alwanni, M.I. Daoud. A Deep Learning Framework for Decoding Motor Imagery Tasks of the Same Hand Using EEG Signals. *IEEE Access* **2019**, 7, 109612–109627.
4. S. Sakhavi, C. Guan, S. Yan. Learning Temporal Information for Brain-Computer Interface Using Convolutional Neural Networks. *IEEE Transactions on Neural Networks and Learning Systems* **2018**, 29 (11), 5619–5629.
5. N. Padfield, J. Zabalza, H. Zhao, V. Masero, J. Ren. EEG-Based Brain-Computer Interfaces Using Motor-Imagery: Techniques and Challenges. *Sensors* **2019**, 19 (6), 1423.
6. G. Xu, X. Shen, S. Chen, et al. A Deep Transfer Convolutional Neural Network Framework for EEG Signal Classification. *IEEE Access* **2019**, 7, 112767–112776.
7. W. Qiao, X. Bi. Deep spatial-temporal neural network for classification of EEG-based motor imagery. *ACM International Conference Proceeding Series* **2019**, 265–272.
8. N. Sharma, A. Upadhyay, M. Sharma, A. Singhal. Deep temporal networks for EEG-based motor imagery recognition. *Scientific Reports* **2023**, 13 (1), 1–12.
9. H.K. Lee, Y.S. Choi. Application of Continuous Wavelet Transform and Convolutional Neural Network in Decoding Motor Imagery Brain-Computer Interface. *Entropy* **2019**, 21 (12), 1199.
10. O. Faust, Y. Hagiwara, T.J. Hong, O.S. Lih, U.R. Acharya. Deep learning for healthcare applications based on physiological signals: A review. *Computer Methods and Programs in Biomedicine* **2018**, 161, 1–13.
11. B. Rim, N.J. Sung, S. Min, M. Hong. Deep Learning in Physiological Signal Data: A Survey. *Sensors* **2020**, 20 (4), 969.
12. R. Ron-Angevin, F. Velasco-Álvarez, Á. Fernández-Rodríguez, et al. Brain-Computer Interface application: auditory serial interface to control a two-class motor-imagery-based wheelchair. *J. NeuroEngineering Rehabilitation* **2017**, 14 (1), 1–16.
13. H. Yu, H. Lu, S. Wang, et al. A General Common Spatial Patterns for EEG Analysis with Applications to Vigilance Detection. *IEEE Access* **2019**, 7, 111102–111114.
14. D.O. Souto, T.K.F. Cruz, K. Coutinho, et al. Effect of motor imagery combined with physical practice on upper limb rehabilitation in children with hemiplegic cerebral palsy. *NeuroRehabilitation* **2020**, 46 (1), 53–63.
15. Y. Li, X.R. Zhang, B. Zhang, et al. A Channel-Projection Mixed-Scale Convolutional Neural Network for Motor Imagery EEG Decoding. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **2019**, 27 (6), 1170–1180.
16. N. Lu, T. Li, X. Ren, H. Miao. A Deep Learning Scheme for Motor Imagery Classification based on Restricted Boltzmann Machines. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **2017**, 25 (6), 566–576.
17. X. Zhao, H. Zhang, G. Zhu, et al. A Multi-Branch 3D Convolutional Neural Network for EEG-Based Motor Imagery Classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **2019**, 27 (10), 2164–2177.
18. P. Sri Ramya, K. Yashasvi, A. Anjum, A. Bhattacharyya, R.B. Pachori. Development of an Effective Computing Framework for Classification of Motor Imagery EEG Signals for Brain–Computer Interface. **2020**, 17–35.
19. Y.R. Tabar, U. Halici. A novel deep learning approach for classification of EEG motor imagery signals. *J. Neural Engineering* **2017**, 14 (1).
20. P.T. Krishnan, A.N. Joseph Raj, P. Balasubramanian, Y. Chen. Schizophrenia detection using MultivariateEmpirical Mode Decomposition and entropy measures from multichannel EEG signal. *Biocybernetics and Biomedical Engineering* **2020**, 40 (3), 1124–1139.
21. M. Murugappan, H. Boon, A.N.J. Raj, G. Krishnan, K. Palanisamy. ECG Morphological Features Based Sudden Cardiac Arrest (SCA) Prediction Using Nonlinear Classifiers. *Lecture Notes in Electrical Engineering* **2020**, 672, 789–801.
22. F. Hassan, S.F. Hussain, S.M. Qaisar. Epileptic Seizure Detection Using a Hybrid 1D CNN-Machine Learning Approach from EEG Data. *Journal of healthcare engineering* **2022**, 2022.
23. S.H. Khan, M. Hayat, F. Porikli. Regularization of Deep Neural Networks with Spectral Dropout. *Neural Networks* **2017**, 110, 82–90.
24. S.A.M. Mane, A. Shinde. StressNet: Hybrid model of LSTM and CNN for stress detection from electroencephalogram signal (EEG). *Results in Control and Optimization* **2023**, 11, 100231.
25. SEED Dataset https://bcmi.sjtu.edu.cn/home/seed/ (accessed Aug 16, 2024).
26. DEAP: A Dataset for Emotion Analysis using Physiological and Audiovisual Signals https://www.eecs.qmul.ac.uk/mmv/datasets/deap/ (accessed Aug 16, 2024).
27. M. Mane. An EEG Recordings Dataset for Mental Stress Detection. **2023**, 1.
28. M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, L.C. Chen. MobileNetV2: Inverted Residuals and Linear Bottlenecks. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* **2018**, 4510–4520.
29. R. Gupta, M.A. Alam, P. Agarwal. Modified Support Vector Machine for Detecting Stress Level Using EEG Signals. *Computational Intelligence and Neuroscience* **2020**, 2020 (1), 8860841.
30. H.-G.; Kim, D.-K.; Jeong, J.-Y. Kim, et al. Emotional Stress Recognition Using Electroencephalogram Signals Based on a Three-Dimensional Convolutional Gated Self-Attention Deep Neural Network. *Applied Sciences* **2022**, 12 (21), 11162.
31. M. Kang, S. Shin, J. Jung, Y.T. Kim. Classification of Mental Stress Using CNN-LSTM Algorithms with Electrocardiogram Signals. *J. Healthcare Engineering* **2021**, 2021 (1), 9951905.