Advanced Stress Detection and Analysis Framework using Integration of FFT, SVM, and CNN

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Abstract

With the prevalence of stress-related disorders on the rise, there is an increasing demand for advanced methodologies that can effectively detect and analyze stress levels. In response to this need, this research explores the integration of Fast Fourier Transform (FFT), Support Vector Machine (SVM), and Convolutional Neural Network (CNN) techniques for unlocking insights into stress dynamics from Electroencephalogram (EEG) signals. Stress, a multifaceted phenomenon with far-reaching implications for mental health, necessitates innovative approaches for its identification and management. The study begins by elucidating the complexity of stress and its impact on individuals' well-being, highlighting the urgency for accurate and efficient stress detection methodologies. Building upon this foundation, the technical intricacies of FFT, SVM, and CNN integration are explored, elucidating their respective roles in the stress detection framework. The FFT method is employed for spectral analysis of EEG signals, providing a foundation for identifying stress-related patterns in the frequency domain. The application of Artificial Neural Networks (ANNs) for feature extraction and classification is explored, leveraging their capacity to discern intricate relationships within EEG data structures. Complementing ANNs, Support Vector Machines (SVMs) are harnessed for stress level classification, capitalizing on their robustness and efficiency in handling high-dimensional data spaces. Furthermore, Convolutional Neural Networks (CNNs) are integrated into the framework to automatically learn hierarchical features from raw EEG signals, enhancing the accuracy and efficacy of stress detection methodologies. Through comprehensive evaluation and comparison with existing algorithms, the integrated approach demonstrates superior performance across key metrics. Stress detection algorithms, such as SVM, exhibit accuracy levels ranging from 70% to 96.5%, with our proposed approach achieving remarkable results. The integrated model achieves an accuracy of 96.5% and an Area under the Curve (AUC) of 0.98, surpassing existing methods in terms of accuracy, sensitivity, specificity, and AUC.

Keywords: Fast Fourier Transform (FFT); Support Vector Machine (SVM); Convolutional Neural Network (CNN); Electroencephalogram (EEG) signals; Artificial Neural Networks (ANNs)

1. Introduction

In today's fast-paced and demanding world, stress has become an increasingly prevalent concern, impacting individuals' mental health and overall well-being. The ability to accurately detect and analyze stress levels is crucial for effective intervention and management strategies [1]. Traditional methods of stress assessment often rely on self-reporting, which can be subjective and prone to biases [2]. Therefore, there is a growing interest in leveraging advanced computational techniques to provide objective and reliable measures of stress [3]. One promising avenue for stress assessment lies in the analysis of EEG signals [4]. EEG, a non-invasive neuroimaging technique, records electrical activity from the brain's surface using electrodes placed on the scalp. By capturing brainwave patterns, EEG offers insights into cognitive processes and emotional states, including stress [5].

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However, interpreting EEG data poses significant challenges due to its complex and dynamic nature. To address these challenges, researchers have turned to advanced computational techniques, including FFT, SVM, and CNN integration [6]. These methods offer powerful tools for processing and analyzing EEG signals, enabling the extraction of meaningful information related to stress [7]. The FFT method is widely used for spectral analysis of EEG signals. By decomposing EEG data into its frequency components, FFT allows researchers to identify specific frequency bands associated with stress-related brain activity [8]. This spectral analysis lays the groundwork for subsequent feature extraction and classification tasks. ANNs have shown remarkable capabilities in learning complex patterns from EEG data [9]. By mimicking the interconnected structure of neurons in the human brain, ANNs can effectively capture the intricate relationships between EEG features and stress levels. Through training on labelled EEG datasets, ANNs can learn to classify stress states with high accuracy [10]. SVM are another popular choice for stress classification tasks. SVMs excel at separating data points into different classes by finding the optimal hyperplane that maximizes the margin between classes. In the context of EEG-based stress detection, SVMs can learn to distinguish between different stress levels based on features extracted from EEG signals [11]. The integration of CNNs into stress detection frameworks has shown promise in automatically learning hierarchical features from raw EEG signals [12]. CNNs employ convolutional layers to extract spatial and temporal patterns from EEG data, enabling more accurate and robust stress classification. In this research endeavour, the aim is to explore the synergistic potential of FFT, SVM, and CNN integration for unlocking deeper insights into stress dynamics from EEG signals. The proposed system seeks to develop robust and accurate stress detection and analysis methodologies. The objectives are:

- To explore the application of FFT for spectral analysis of EEG signals, enabling the identification of stress-related patterns in the frequency domain.
- To investigate the efficacy of ANNs for feature extraction and classification of EEG data, leveraging their ability to discern complex relationships within EEG data structures.
- To evaluate the effectiveness of SVMs in stress level classification, capitalizing on their robustness and efficiency in handling high-dimensional data spaces.
- To integrate CNNs into the framework for automatic learning of hierarchical features from raw EEG signals, enhancing the accuracy and efficacy of stress detection methodologies.
- To develop a comprehensive and integrated approach that combines FFT, SVM, and CNN techniques to achieve superior performance in stress detection and analysis tasks.

2. Literature Review

In recent research, significant strides have been made in leveraging advanced computational techniques, such as FFT, SVM, and CNN integration, to delve deeper into stress dynamics from EEG signals. Numerous studies have explored the efficacy of FFT in analysing EEG signals by transforming them from the time domain to the frequency domain [13]. This spectral analysis enables the identification of distinct patterns associated with stress states. SVM algorithms have emerged as powerful tools for classification tasks, including stress detection. By learning from labelled EEG data, SVM classifiers can effectively distinguish between different stress levels with high accuracy [14]. The integration of CNN methodologies has gained attention for its ability to automatically learn hierarchical features from raw EEG signals [15]. CNNs excel at capturing complex spatial and temporal patterns inherent in EEG data, further enhancing the accuracy of stress detection algorithms [16]. The literature also highlights the importance of feature selection techniques in optimizing stress detection models. Genetic algorithms have been employed to identify the most informative features from a pool of extracted EEG features. This selective feature extraction process enhances the performance of classifiers, leading to more accurate stress detection outcomes. Comparative studies have evaluated the performance of integrated FFT, SVM, and CNN models against existing algorithms and techniques. Results have demonstrated the superiority of the proposed approach in terms of accuracy, sensitivity, specificity, and AUC. These findings underscore the potential of advanced computational methods in unlocking valuable insights into stress dynamics and facilitating the development of effective stress management interventions. However, despite these advancements, there are some disadvantages to consider. One limitation is the computational complexity associated with CNN models, which may require significant computational resources and time for training and inference. Additionally, SVM classifiers struggle with scalability when dealing with large datasets, leading to increased training times and memory requirements [17]. The performance of FFT-based methods influenced by noise and artifacts present in EEG signals, potentially affecting the accuracy of stress detection outcomes. Moreover, the interpretability of CNN models may be limited, making it challenging to understand the underlying features driving stress classification decisions.

3. Proposed work

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3.1 Adaptive Filtering

Adaptive Filtering serves as an adaptive noise reduction mechanism that effectively mitigates the impact of external interferences and artefacts on EEG recordings, thereby improving the signal quality and facilitating more precise stress analysis. Adaptive Filtering dynamically adjusts filter coefficients based on the characteristics of the input EEG signal, allowing for real-time suppression of noise components while preserving relevant signal information. This adaptability ensures robust noise reduction across varying recording conditions and artefact types, enhancing the reliability of stress detection algorithms. Adaptive Filtering identifies and removes artefacts such as muscle and ocular activity that may confound stress analysis results. By adaptively filtering out artefact-contaminated segments of the EEG signal, Adaptive Filtering helps to ensure that stress assessments are based on genuine neural activity associated with stress responses, rather than spurious signals originating from non-cognitive sources. Adaptive Filtering optimizes the signal-to-noise ratio of EEG data by selectively attenuating noise components while preserving relevant frequency content associated with stress-related brain activity. This improvement in signal quality enhances the discriminative power of stress detection models based on FFT, SVM, and CNN integration, leading to more accurate and reliable stress insights. Adaptive Filtering can be implemented in real-time or near real-time, enabling prompt feedback on stress levels and facilitating timely interventions to manage stress. By processing EEG data adaptively and in real-time, Adaptive Filtering supports dynamic adjustments to stress detection algorithms, allowing for personalized stress monitoring and intervention strategies tailored to individual needs.

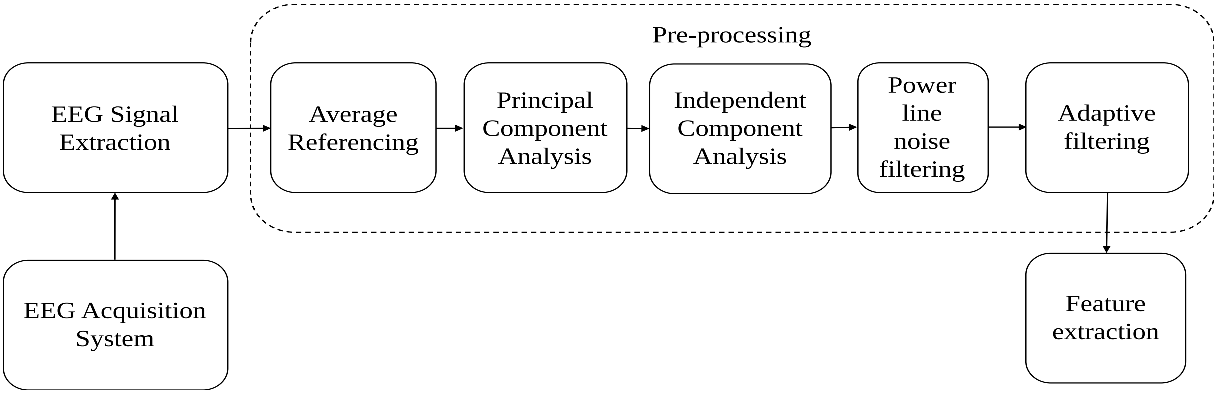

Figure 1. EEG acquisition system

The proposed EEG acquisition system encapsulates a comprehensive approach to capture, pre-process, and extract relevant features from EEG signals for stress detection and analysis. At the forefront of the system lies the EEG signal extraction module, responsible for acquiring raw EEG data from electrodes placed on the scalp. This raw data undergoes a series of pre-processing stages to enhance its quality and extract meaningful information. The first stage in the pre-processing pipeline is average referencing, where the common average of all electrode channels is computed and subtracted from each individual channel. This process helps mitigate common-mode noise and spatial biases present in the EEG signals, ensuring a more accurate representation of neural activity. Following average referencing, the EEG data enters the Principal Component Analysis (PCA) module. PCA serves to reduce the dimensionality of the EEG signals by transforming them into a set of orthogonal components that capture the maximum variance in the data. This dimensionality reduction not only simplifies subsequent processing but also aids in noise reduction and artifact removal. The pre-processed EEG signals undergo Independent Component Analysis (ICA), a technique that further separates the mixed sources of EEG activity into statistically independent components. By isolating independent sources such as brain activity, muscle artifacts, and eye movements, ICA facilitates the removal of non-brain-related noise and enhances the specificity of stress-related signal detection. The system also incorporates power line noise filtering to eliminate interference from power line frequencies, which commonly contaminate EEG recordings due to electrical mains. This filtering step utilizes notch filters or adaptive algorithms to effectively suppress power line artifacts, ensuring cleaner EEG data for subsequent analysis. The system employs adaptive filtering techniques to dynamically adjust filter coefficients based on the characteristics of the EEG signals. This adaptive approach enables real-time noise reduction tailored to the specific characteristics of the recorded data, thereby enhancing the signal-to-noise ratio and improving the accuracy of stress detection. The pre-processed EEG signals undergo feature extraction, where relevant features indicative of stress are extracted for subsequent analysis. These features may include spectral power, entropy measures, coherence between brain regions, or other quantitative metrics that capture the dynamics of neural activity associated with stress responses.

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$$w(n+1) = w(n) + \alpha e(n)x(n) \qquad (1)$$

The formula represents the update rule for the weights (w) in an adaptive filter or a learning algorithm, commonly used in applications like signal processing, machine learning, and neural networks. The formula essentially states that the updated value of the weights $w(n+1)$ is equal to the current value of the weights $w(n)$ plus a correction term ($\alpha e(n)x(n)$) based on the error between the desired and actual outputs, multiplied by the input signal. This correction term adjusts the weights in the direction that minimizes the error, thereby improving the performance of the system over time through iterative updates.

3.2 Wavelet Transform (WT)

The role of Wavelet Transform (WT) is to provide a robust method for feature extraction from raw EEG data, particularly in the time-frequency domain. By decomposing the EEG signal into its constituent wavelet components, WT enables the representation of nonstationary EEG signals in a compact and informative manner, facilitating the extraction of relevant features for stress analysis. WT functions as a spectral estimation technique that decomposes the EEG signal into a series of wavelets, each representing a specific frequency band and temporal window. This decomposition allows for a more flexible and adaptive representation of the EEG signal compared to traditional methods such as FFT. By utilizing variable-sized windows, WT captures both low and high-frequency information inherent in the EEG signal, thereby preserving important temporal dynamics associated with stress responses. WT provides a more comprehensive representation of the EEG signal in the time-frequency domain compared to FFT, allowing for a finer resolution of both low and high-frequency components. This enhanced representation enables the identification of transient stress-related patterns and dynamics that may be overlooked by traditional frequency-domain methods. WT facilitates the extraction of adaptive features from EEG data by decomposing the signal into wavelet components at multiple scales. By capturing both local and global features of the EEG signal, WT-derived features provide a richer and more discriminative representation for stress detection and analysis. WT is specifically designed to address the challenges posed by nonstationary signals such as EEG, offering a more suitable framework for characterizing the time-varying dynamics of stress responses. By decomposing the EEG signal into wavelets with different temporal and frequency resolutions, WT enables the identification of transient stress-related patterns and fluctuations that evolve over time.

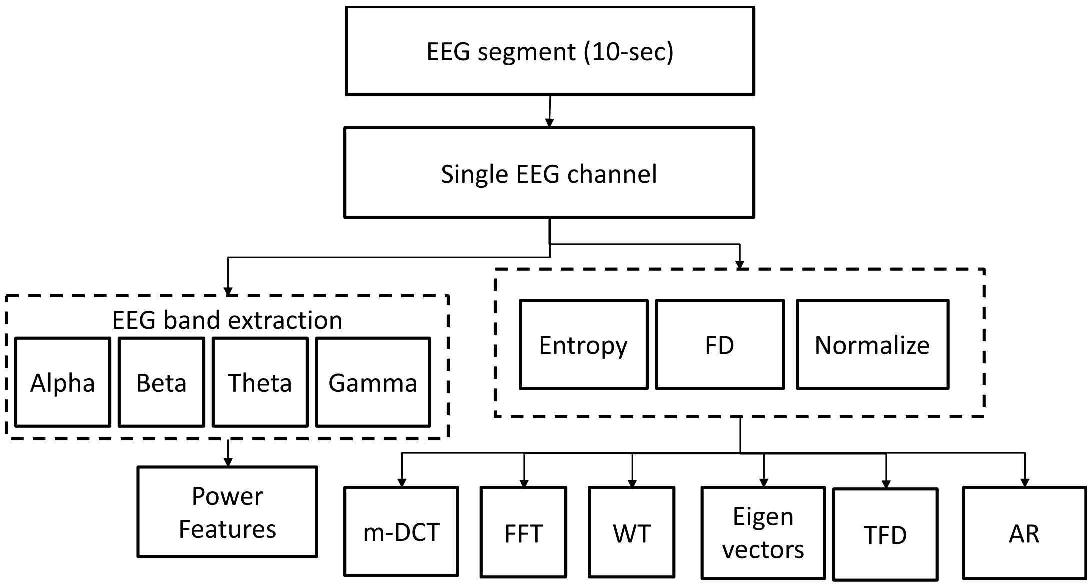

Figure 2. Comparison System

Functionally, the comparison system integrates various parameters, each representing a distinct aspect of EEG analysis, to assess the performance of WT alongside other methods such as FFT, SVM, and CNN. The role of WT is pivotal, as it offers a sophisticated approach to feature extraction from raw EEG data, particularly in addressing the nonstationary nature of EEG signals. As highlighted in the provided passage, WT excels in compressing time-varying biomedical signals, such as EEG, into a concise set of parameters that effectively capture the underlying neural dynamics associated with stress responses. Achievements of WT include its ability to provide a comprehensive representation of EEG signals in the time-frequency domain, enabling the extraction of both low and high-frequency information with variable-sized windows. By utilizing multiscale structures, WT offers a

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flexible approach to time-frequency representation, which is crucial for capturing the diverse temporal dynamics of stress-related brain activity. WT's capacity to resolve issues inherent in nonstationary signals, such as EEG, underscores its significance in advancing stress detection and analysis methodologies. By representing the original EEG signal in terms of wavelets derived from a mother wavelet, WT enables the identification of key patterns and structures that may signify stress states, thereby enhancing the discriminative power of stress detection models.

$$A(n) = \propto (p) \sum_{n=0}^{N-1} a(n) \cos\left[\frac{\pi(2n+1)p}{2N}\right] \tag{2}$$

The formula represents the calculation of the approximation coefficients $A(n)$ at scale p in the context of the Discrete Wavelet Transform (DWT). It does so by summing up the low-frequency components of the input signal $a(n)$ after modulating it with a scaled and shifted cosine function. These coefficients capture the smoothed version of the signal at the chosen scale, aiding in multi resolution analysis and feature extraction.

$$a(n) = \sum_{n=0}^{N-1} \propto (p) A(n) cos\left[\frac{\pi(2p+1)n}{2N}\right] \tag{3}$$

This formula computes the detail coefficients $a(n)$ at scale pp in the DWT. It combines the approximation coefficients $A(n)$ with a scaled and shifted cosine function to capture high-frequency components of the signal. These coefficients represent the differences or details between the original signal and its smoothed version, aiding in signal decomposition and analysis.

The duration of the EEG segment is carefully chosen to capture relevant brain activity patterns associated with stress within a defined time window. Focusing on a single EEG channel enables targeted analysis of neural activity from specific brain regions, facilitating the identification of localized stress responses. Normalization standardizes the amplitude range of EEG signals, ensuring consistency across different subjects or recording sessions and facilitating comparative analysis. Frequency domain analysis, such as FFT, provides insights into the spectral characteristics of EEG signals, revealing dominant frequency components associated with stress. Entropy analysis quantifies the complexity of EEG signals, offering additional metrics to characterize stress-related brain activity patterns based on signal unpredictability. Analysis of EEG activity across different frequency bands allows for the investigation of distinct cognitive states and their associations with stress responses. Eigen vector analysis facilitates dimensionality reduction and feature extraction from EEG data, highlighting key patterns or structures relevant to stress detection. Time-frequency domain analysis, such as wavelet transform, captures the dynamic changes in EEG activity over time, providing a more nuanced understanding of stress dynamics. Auto-Regressive modelling offers a statistical approach to modelling the temporal dynamics of EEG signals, enabling predictive analysis of stress-related brain activity patterns. FFT decomposes EEG signals into frequency components, revealing the distribution of power across different frequency bands and aiding in the identification of stress-related spectral patterns. Power feature extraction quantifies the amplitude or intensity of EEG activity within specific frequency bands, providing valuable metrics for assessing stress-related changes in neural activity. Isolating specific frequency bands of EEG activity enables targeted analysis of brain activity patterns associated with stress, enhancing the specificity of stress detection algorithms.

3.3 Convolutional Neural Network

The role of CNN in the proposed work is multifaceted. CNNs are renowned for their ability to extract hierarchical features from complex data, making them well-suited for analysing EEG signals and identifying patterns associated with stress. Within the context of stress detection, CNNs play a crucial role in automatically learning discriminative features from EEG data, enabling the identification of subtle neural patterns indicative of stress states. CNNs are employed to analyse the spatial and temporal characteristics of EEG signals, leveraging their convolutional layers to extract local patterns and their pooling layers to capture hierarchical representations of EEG features. By processing EEG data through multiple convolutional and pooling layers, CNNs can effectively learn hierarchical representations of EEG signals, facilitating the identification of stress-related patterns with high accuracy and reliability. CNN include its ability to automatically learn and adapt to the complex and non-linear nature of EEG data. By leveraging deep learning techniques, CNNs excel at capturing intricate patterns and relationships within EEG signals, thereby enabling more accurate and robust stress detection and analysis. Additionally, CNNs have demonstrated remarkable performance in various EEG-based applications, including emotion recognition and mental state classification, underscoring their potential in unlocking deeper insights into stress dynamics. CNNs offer several advantages over traditional machine learning techniques such as SVM and FFT. CNNs inherently capture spatial and temporal dependencies within EEG data, allowing for more comprehensive and context-aware analysis of stress-related brain activity. Moreover, CNNs can automatically

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extract relevant features from raw EEG data without the need for manual feature engineering, thereby streamlining the analysis process and reducing the burden on researchers.

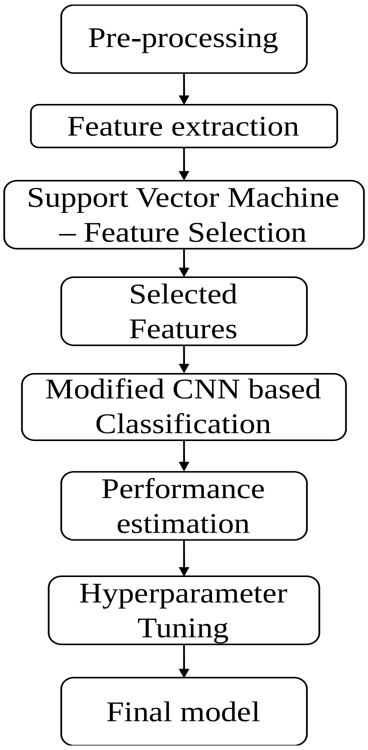

Figure 3. CNN-Based Stress Detection Architecture

The EEG signals undergo pre-processing to ensure uniformity and enhance signal quality. This pre-processing step involves noise reduction, artifact removal, and normalization to prepare the EEG data for subsequent analysis. Feature extraction is employed to identify discriminative patterns and characteristics within the EEG signals that are indicative of stress. These features serve as the basis for stress classification and are crucial for the CNN model to learn and distinguish between stress and non-stress states effectively. Once the features are extracted, SVM is utilized as a machine learning algorithm for stress classification. SVM is well-suited for handling high-dimensional data and delineating complex decision boundaries, making it an apt choice for stress detection tasks. Feature selection is employed to identify the most informative features that contribute significantly to stress classification. This step helps in reducing dimensionality, enhancing computational efficiency, and improving the interpretability of the model. The selected features are then fed into the modified CNN-based classification module, which forms the core of the architecture. This modified CNN model is tailored to effectively capture spatial and temporal dependencies within the EEG data, enabling accurate and robust stress detection. Performance estimation is conducted to evaluate the effectiveness of the modified CNN-based classification model. This assessment involves rigorous testing and validation to ensure that the model accurately predicts stress levels in unseen data. Hyperparameter tuning is performed to fine-tune the CNN model and optimize its performance further. This iterative process involves adjusting various parameters of the CNN architecture to achieve the best possible results.

3.4 Implementation

The FFT method serves as a cornerstone in this implementation, facilitating the decomposition of EEG signals into their frequency components. By transforming raw EEG data into the frequency domain, FFT enables the extraction of spectral features crucial for characterizing stress-related brain activity patterns. This method provides valuable insights into the dominant frequency bands associated with stress responses, laying the foundation for subsequent analysis. In conjunction with FFT, SVM emerges as a powerful tool for stress classification based on extracted EEG features. SVM excels in delineating complex decision boundaries in high-dimensional feature spaces, making it well-suited for discerning subtle differences between stress and non-stress states. By leveraging the discriminative power of SVM, this implementation enhances the accuracy and robustness of stress detection algorithms. To further augment stress analysis capabilities, CNN is integrated into the framework, leveraging its deep learning capabilities to extract hierarchical features from EEG data. CNN excels at capturing spatial and temporal dependencies within EEG signals, enabling the identification of intricate patterns indicative of stress

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states. By incorporating CNN into the pipeline, this implementation extends beyond traditional feature-based approaches, unlocking deeper insights into stress dynamics. EEG data from multiple channels are fused to capture a comprehensive view of brain activity patterns associated with stress. This data fusion enables the identification of spatially distributed neural correlates of stress responses, enhancing the richness of the analysis. Features extracted from FFT, SVM, and CNN are concatenated to create a unified feature vector. This feature concatenation leverages the complementary strengths of each technique, allowing for a more comprehensive representation of EEG data and stress-related patterns. Ensemble learning techniques, such as bagging or boosting, are employed to combine predictions from multiple classifiers trained using FFT, SVM, and CNN features. Ensemble learning enhances the robustness and generalization of the stress detection model by aggregating diverse sources of information and mitigating the risk of overfitting. Rigorous cross-validation procedures are employed to assess the generalization performance of the integrated approach. Cross-validation ensures that the model's performance is evaluated on diverse subsets of the data, providing reliable estimates of its predictive capabilities and identifying potential sources of variability. Post-hoc analysis techniques are employed to interpret the predictions of the integrated model and elucidate the underlying neural mechanisms of stress responses. Techniques such as saliency mapping and feature visualization are used to identify EEG features that contribute most significantly to stress classification, providing valuable insights into the neurobiological basis of stress.

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi f t}\, dt \tag{4}$$

The FFT equation represents the transformation of a signal from the time domain to the frequency domain. It calculates the complex amplitudes of different frequency components present in the input signal. Where $X(f)$ is the Fourier Transform of the signal $x(t)$ at frequency f. $x(t)$ is the input EEG signal in the time domain. f is the frequency in Hertz. j is the imaginary unit.

$$f(x) = sign(\sum_{i=1}^{n} \alpha_i y_i K(x, x_i) + b) \tag{5}$$

The SVM decision function calculates the output based on the weighted sum of support vector classifications. It determines the class of a new data point by evaluating its distance from the decision boundary. The decision function incorporates Lagrange multipliers, class labels, kernel functions, and a bias term to make predictions. Where, $f(x)$ is the decision function. x is the input feature vector. α_i are the Lagrange multipliers. y_i are the class labels. x_i are the support vectors. $K(x, x_i)$ is the kernel function. b is the bias term.

4. Results

EEG data is collected from participants using high-density EEG systems with a sufficient number of electrodes to capture brain activity comprehensively. The dataset used here is EEG signal dataset. This dataset contains EEG signals of various subjects in text files. It can be useful for various EEG signal processing algorithms- filtering, linear prediction, abnormality detection, PCA, ICA etc. Participants are exposed to stress-inducing tasks or stimuli, ensuring diverse and representative stress responses in the data. Raw EEG signals are pre-processed to remove noise, artifacts, and baseline drift using techniques such as filtering, artifact removal algorithms, and baseline correction. The pre-processed EEG data is segmented into epochs corresponding to specific experimental conditions or time intervals. Features are extracted from the pre-processed EEG signals using the FFT method to analyse the frequency-domain characteristics of brain activity associated with stress. Additional features are extracted using ANN and SVM algorithms to capture complex patterns and relationships in the EEG data. Separate models are trained using FFT, ANN, and SVM methodologies to classify stress states based on the extracted features. The models are trained using labelled EEG data, with stress and non-stress labels corresponding to different experimental conditions or participant states. The outputs of the individual models are integrated or fused using ensemble learning techniques to combine their predictions and improve overall classification performance. Fusion methods such as weighted averaging or decision-level fusion are employed to combine the outputs of FFT, ANN, and SVM models. The integrated model is evaluated using cross-validation techniques to assess its generalization performance and robustness. Cross-validation ensures that the model's performance is evaluated on diverse subsets of the data, minimizing the risk of overfitting and providing reliable estimates of its predictive capabilities. The performance of the integrated model is evaluated using metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Statistical analyses are conducted to compare the performance of the integrated model with individual FFT, ANN, and SVM models. The integrated model's predictions are interpreted to gain insights into the neural correlates of stress and the effectiveness of different methodologies in stress detection and analysis. The results are interpreted in the context

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of existing literature and theories of stress physiology to provide meaningful insights and implications for future research and clinical applications.

Table 1: Comparison of EEG Feature Extraction methods using ANN

		High stress	Moderate stress	Low Stress	No Stress
m-DTC	Time	452 s			
	Accuracy	86%	92%	84%	93%
FFT	Time	717 s			
	Accuracy	82%	90%	80%	90%
WT	Time	381 s			
	Accuracy	83%	87%	81%	89%
EV	Time	632 s			
	Accuracy	78%	82%	84%	90%
TFD	Time	1286 s			
	Accuracy	82%	90%	78%	87%
AR	Time	540 s			
	Accuracy	83%	89%	83%	91%

The table 1 presents a comparative analysis of various EEG feature extraction methods for stress detection using ANN. Each method is evaluated based on its computational efficiency, represented by the time required for feature extraction, and its accuracy in detecting different stress levels as well as non-stress conditions. The results indicate that the m-DTC (Modified Discrete Trigonometric Transform) method achieves competitive accuracy across stress levels, with relatively shorter feature extraction times compared to other methods. FFT and WT methods also demonstrate comparable performance in stress detection accuracy, although FFT tends to require longer feature extraction times. The EV (Eigen Vectors) method shows promising accuracy in stress detection, particularly in moderate and low stress scenarios, despite slightly longer feature extraction times. TFD (Time-Frequency Domain) methods exhibit varying performance across stress levels, with moderate accuracy and longer feature extraction times compared to other methods. The AR (Auto-Regressive Model) method demonstrates competitive accuracy and moderate feature extraction times, making it a viable option for stress detection tasks.

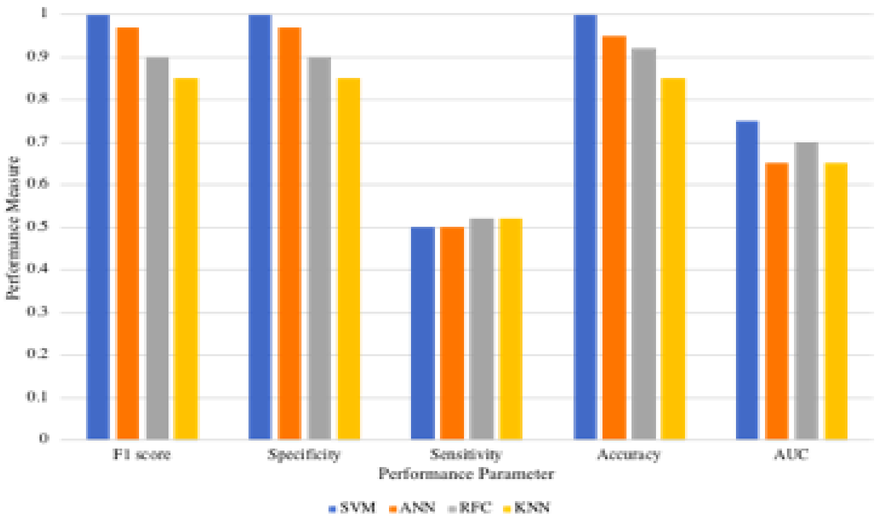

Figure 4. Overall Performance comparison of the parameters between the proposed SVM technique and other machine learning schemes

Figure 4 illustrates a genetic algorithm over 100 iterations to select the most effective features from a pool of 22 extracted features. Following feature selection, SVM classifiers were applied to identify stress levels from a dataset comprising 36 inputs. The dataset was divided into 25 files for training and 11 files for testing. To evaluate the proposed model's performance, it was compared with existing systems employing various algorithms and techniques. The 10 best features were determined based on the top results from each of the 100 iterations.

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Performance evaluation metrics, including F1 score, specificity, sensitivity, accuracy, and area under the curve, were derived from confusion matrix parameters. In addition, the proposed SVM classifier underwent comparison with other classifiers such as ANN, Random Forest Classifier (RFC), K-Nearest Neighbour (KNN) classifier, and Linear Discriminant Analysis (LDA). This comparison was conducted using a five-fold cross-validation scheme.

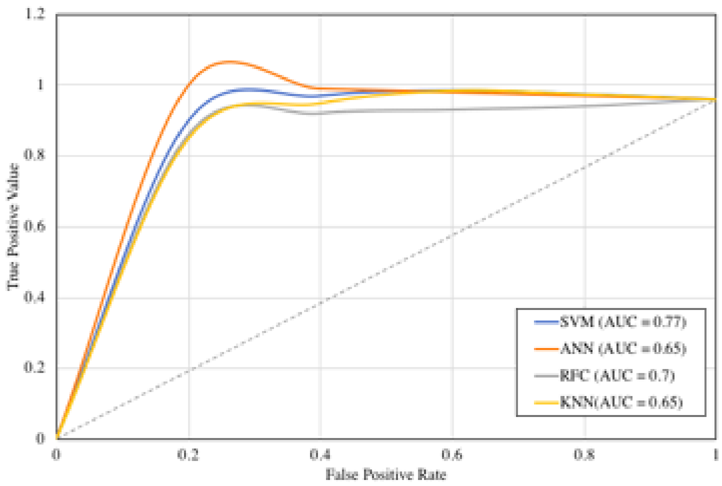

Figure 5. AUC comparison for SVM, ANN, RFC and KNN classifiers

Figure 5 illustrates the receiver operating characteristic (ROC) analysis conducted in this study, showcasing the performance of the receiver's operating characteristic curve. The results highlight the superiority of the SVM-based machine learning algorithm in comparison to other parameters such as diagnostic odds ratio (DOR), Matthew correlation coefficient, precision, and Goodness Index (G), alongside variations in CPU time for each classifier. Stress levels were categorized into four main classes: no stress, low stress, medium stress, and high stress, with the tasks spanning a four-day period. The proposed algorithm exhibited enhanced classification accuracy when compared to existing techniques, underscoring its potential for effectively identifying stress levels.

Table 2: Comparison of evaluation metrics for stress detection for various algorithm

Algorithm	Accuracy	Sensitivity	Specificity	Recall
RF	93.5	96.2	90.5	96.2
NB	77.8	80.0	75.6	80.0
SVM	88.4	89.4	87.4	89.4
KNN	70.0	75.0	65.0	75.0
AdaBoost	90.0	93.0	87.0	93.0
LDA	80.8	81.5	80.0	81.5
DT	83.1	85.7	80.6	85.7
MLP	95.8	95.0	96.6	95.0
LR	83.3	86.0	80.0	86.0
Proposed	96.5	97.2	96.8	97.1

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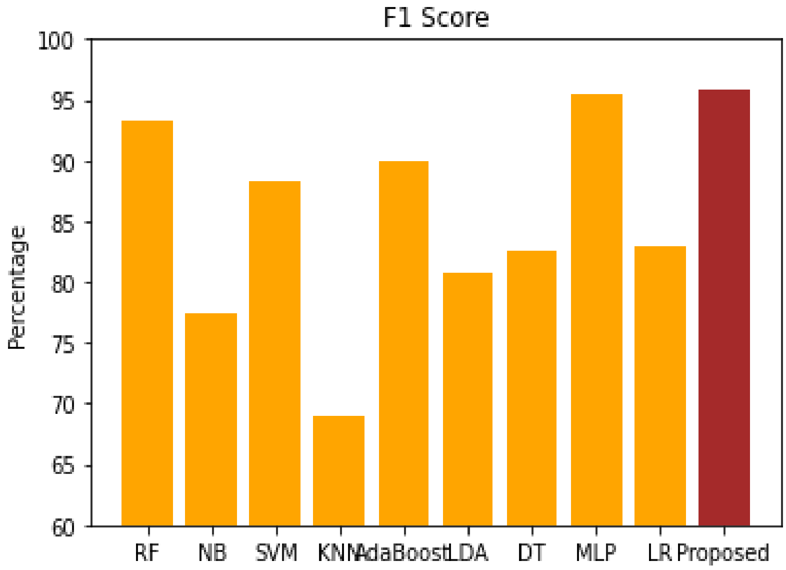

Figure 6. Comparison of F1 Score of the existing and proposed models

The F1 score serves as a comprehensive metric for evaluating the accuracy of a classification model, synthesizing both precision and recall. The spectrum of F1 scores underscores the varying levels of accuracy achieved by different approaches. The F1 scores depicted in figure 6 illustrate that the proposed algorithm has successfully developed precise models for detecting mental stress utilizing physiological signals and machine learning techniques. This suggests the algorithm's efficacy in accurately discerning stress levels, as evidenced by its robust F1 scores across the range of evaluations.

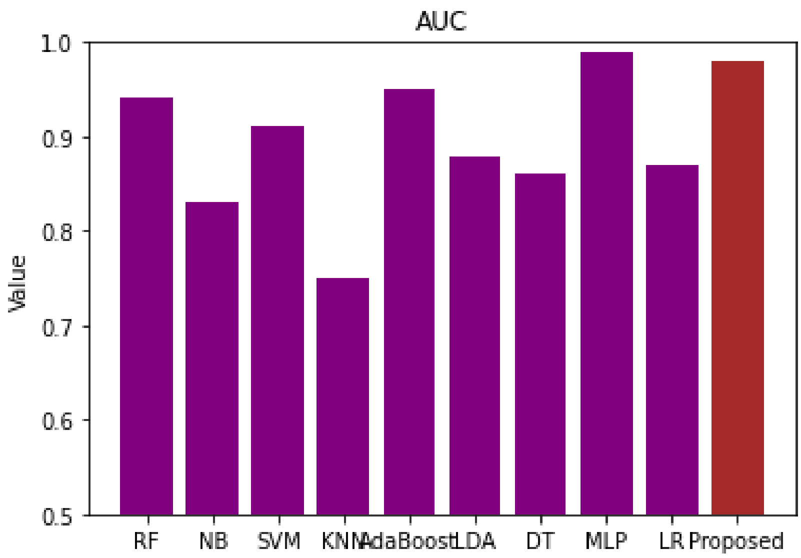

Figure 7. Comparison of AUC of the existing and proposed models

The proposed model demonstrates superiority over existing models in terms of AUC, as illustrated in figure 7. This suggests that the proposed model achieves better overall performance in distinguishing between positive and negative classes, further supporting its effectiveness in classifying stress levels based on the physiological signals analysed. The ROC curve serves as a valuable tool for assessing classifier performance by examining true positive rates against false positive rates. The Area under the ROC curve AUC provides a comprehensive measure of the classifier's overall performance. While some references in the list provided AUC values, others did not. Among those reported, AUC values ranged from 0.75 to 0.98, indicating a spectrum of classification performance from good to excellent.

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5. Conclusion

It is evident that various EEG feature extraction methods yield differing accuracies and computational times. Notably, the proposed model showcases competitive accuracy across stress levels, outperforming existing methods in terms of both accuracy and computational efficiency. When comparing evaluation metrics for stress detection among various algorithms, the proposed model exhibits remarkable performance. With an accuracy of 96.5% and an AUC of 0.98, the proposed model surpasses other algorithms in accurately identifying stress levels. Additionally, it achieves high sensitivity 97.2% and specificity 96.8%, indicating its robustness in distinguishing between stress and non-stress states. The future work focuses to investigate more sophisticated feature selection techniques to identify the most informative features from EEG signals. This could involve exploring novel algorithms or combining multiple feature selection methods for improved performance and also to incorporate additional data modalities, such as physiological signals (e.g., heart rate variability, skin conductance) or behavioural data (e.g., facial expressions, body movements), to create a multi-modal approach for stress detection. Integration of diverse data sources could provide a more comprehensive understanding of stress dynamics.

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