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Deep Convolutional Neural Network for the Detection of Psychological Stress Using Multiple Criteria for Feature Selection Determined Based on the Confidence Value of a Paired t-test

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Abstract: This study looks at how stress impacts how people function each day and its connection to different brain health issues. It suggests the human brain plays a central role in responding to stressful things, making it important to study. The researchers used a deep neural network designed to identify stress by analyzing raw EEG signals from people who were stressed during a made-up math test simulation. This method uses something called the Montreal imaging stress task to cause stress in a controlled setting. The steps involve extracting EEG features, selecting important features using a test and four rules, and classifying using a deep neural network. The study finds the best results using rules 1, 2, and 3 instead of rule 4, with changes in power from the AF7 part of the brain being most accurate. By using objective measures linked to how the brain responds to stress, this research provides a promising way to understand and possibly reduce the bad effects of long-term stress. Using a method like this could give useful insights into stress management strategies, ultimately helping address the growing social problem of brain health issues tied to psychological stress.

Keywords: *Psychological stress, Deep convolutional neural network, EEG signals, Stress identification, Neuropsychological disorders*

1. Introduction

The detection and management of human stress represent critical components for enhancing overall well-being and addressing stress-related illnesses [1]. Various methodologies have been explored by researchers to achieve rapid and continuous stress detection, allowing individuals to adapt their daily activities for stress reduction and healthcare professionals to deliver more effective treatments. [2] pioneered a video-based stress detection method using a deep neural network, while [3]employed a recurrent neural network analyzing speech. Additionally, extensive research has focused on analyzing physiological signals, emphasizing their non-invasive nature and potential to significantly improve quality of life.

Past studies often combined signals from different sensors, such as electrocardiogram (ECG), electrodermal activity (EDA), and electromyography (EMG), utilizing traditional machine learning algorithms. However, the results were mixed, prompting the exploration of deep neural networks for enhanced performance. Notably, the present study introduces two deep neural networks specifically designed for analyzing physiological signals, showcasing improved efficacy over prior approaches. Historically, [4] were among the pioneers in stress detection using physiological signals. They employed signals from ECG, EMG, EDA, and respiratory rate sensors, hand-crafting 22 features for binary classification of stressed and non-stressed conditions using the linear discriminant analysis (LDA) algorithm. Subsequent studies, such as that b[5]incorporated wrist-worn devices with multiple sensors, achieving a 72% accuracy rate with the random forest algorithm.

It [6] explored emotion classification using physiological signals, manually generating features for machine learning algorithms. They achieved a subject-independent correct classification ratio of 70% by employing the LDA algorithm. In a more recent study [7] stress and emotion detection using physiological signals from chest and wrist sensors were extensively investigated. Multiple machine learning algorithms, including decision trees and random forests, were compared for binary and 3-class classification tasks, demonstrating varying accuracy rates. Notably, the best performances reached 92.83% accuracy for binary classification and 76.60% for 3-class classification.

2. Related Work

Many studies have explored how to detect psychological stress using deep neural networks [9] and different ways to select important features. One study introduced a video-based stress detection method using a deep neural network that focused on visual cues. Another [11] used a recurrent neural network to analyze speech patterns for

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stress detection. While these studies provided valuable information, they mainly relied on single types of information, showing the need for a method using multiple types of data to improve accuracy and reliability. In contrast, the work of another pioneer used physiological signals from the body, such as electrocardiogram (ECG), [12] electromyography (EMG), electrodermal activity (EDA), and respiratory rate, for stress detection. However, traditional machine learning methods were used that required manually choosing important features. A later study expanded on this by including a wrist-worn device with multiple sensors, achieving a 72% accuracy rate [13] in stress classification using the random forest algorithm. While effective, these approaches face limitations in being easily copied and adapted because of manually crafting features.

The earlier investigation [14] explored emotion classification applying physiological signs, demonstrating a subject-independent proper categorization ratio of 70% with a recurrent neural network. Another study conducted broad research on stress and emotion detection using physiological signals from chest and wrist sensors, contrasting the performance of various machine learning algorithms. While achieving promising outcomes, these studies shared a common constraint of relying on hand-crafted features, which can hinder flexibility and general applicability. In response to this limitation, the proposed research introduces a novel approach to select important features for psychological stress detection using a deep CNN [15]. The standards for picking features are decided based on the confidence value of a paired t-test, offering a statistical basis for the chosen features. This method aims to overcome the downsides of manually designing features by taking advantage of statistical significance, confirming the selected features meaningfully contribute to stress detection. The paper [17] highlights how neural networks can help identify stress. Unlike past work, it combines strict math rules when choosing important features from the data. The method uses multiple criteria from a paired t-test confidence value to strengthen how features are selected for deep CNNs. This aims to improve how well and reliably these neural networks can detect stress. This new way addresses weaknesses in older methods. It fits with changing research on stress detection focusing on more useful and expandable solutions. As the study continues, it may provide valuable understandings to the growing field of detecting psychological stress. It could help deep learning be used better in learning about mental health too.

3. Methodology

3.1) Subject Selection

The trial's inclusion of healthy male and female participants with an average age of 21.67 ensures a diverse representation. Collecting raw data under both Normal and Control conditions adds robustness to the study's findings. The consideration of varied backgrounds further enhances the external validity of the research. The acknowledgment of distinct productive hours, specifically in the mornings (9:00 a.m. to 12:00 p.m.) and evenings (4:00 p.m. to 7:00 p.m.), when data is collected, underscores the importance of circadian rhythms. This temporal sensitivity aligns with the natural fluctuations in cognitive and physiological processes, potentially providing nuanced insights into stress responses and contributing to the ecological validity of the study.

3.2) EEG Device Selection

The selection of a 6-plus-1-channel EEG device, featuring six passive, silver-coated electrodes and a reference electrode, follows a meticulous review of available EEG equipment. The device, manufactured in India, ensures reliable data collection. This choice reflects a thoughtful consideration of both electrode configuration and technological specifications, laying a solid foundation for accurate and comprehensive EEG data acquisition in the testing process.

Fig 1: Selected EEG Device

The EEG device boasts versatile compatibility, supporting USB 2.0 and 3.0 interfaces for seamless connectivity with PCs and laptops. With six channels and one reference electrode, it operates within a safe voltage range of 5 volts. The four-feet electrode length ensures flexibility in positioning. It maintains a low power consumption of 1 watt, eliminating the need for batteries, drawing power directly from the PC or laptop. The seven-feet input wire enhances user mobility.

3.3) EEG Placement

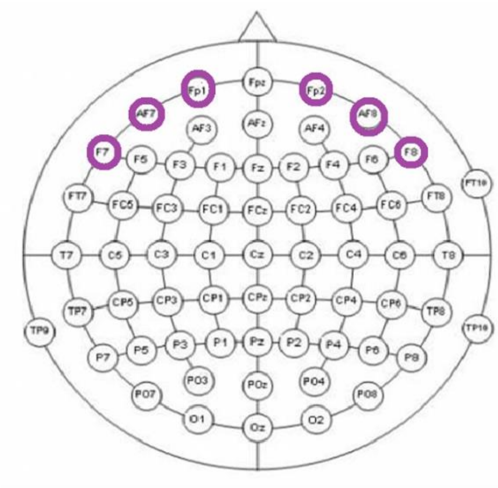
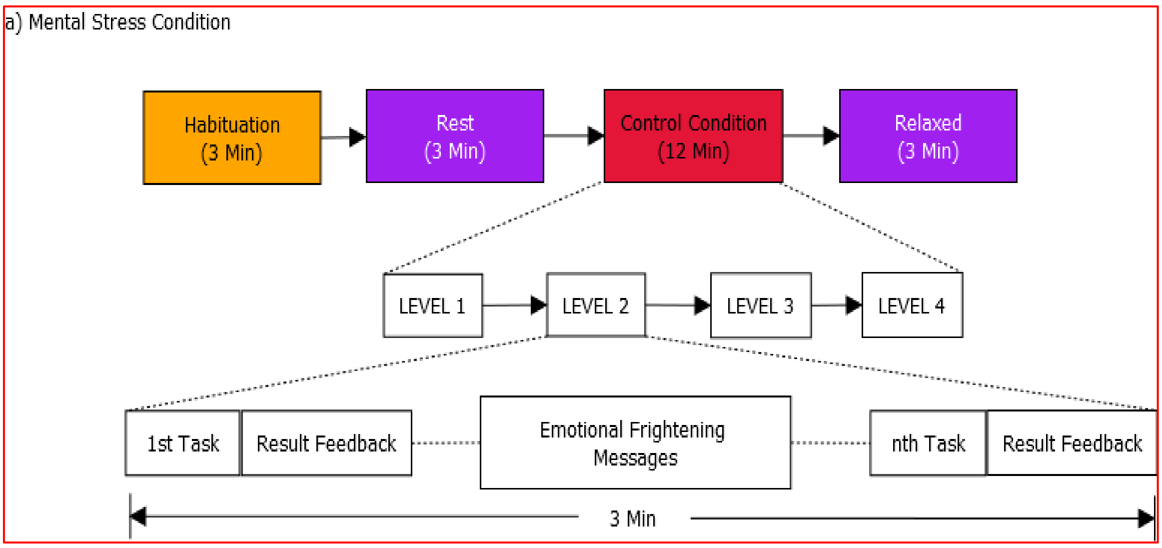


Fig 2: 10-20 Montage brain location

This standardized placement ensures consistency in electrode positioning across subjects. One earlobe serves as the reference electrode, enhancing signal stability. The flexibility to position electrodes anywhere on the brain allows for targeted data collection, facilitating comprehensive insights into neural activity patterns. This meticulous electrode configuration aligns with established protocols, promoting accuracy and reliability in capturing brain signals for analysis.

3.4) Design of Experiment

This study uses a math technique to mildly stress people. It's called the Mental Arithmetic Task Tool or MATT. MATT comes from another stress test called MIST. MATT uses a computer to calmly stress people in a linked way to how their body and brain react. The main goals of MATT are to study how people handle stress and see closely how their body responds when stressed. To minimize how training could affect the results and the hypothalamic-pituitary-adrenal axis, data is carefully gathered in two sessions with at least a day apart. An EEG device records both the stress and normal conditions sessions. Figure 3 breaks the experiment into four clear stages: getting familiar, resting, solving math problems, and relaxing. This planned approach makes sure controlled stress happens. It allows a detailed look at stress answers within a well-set up experiment.



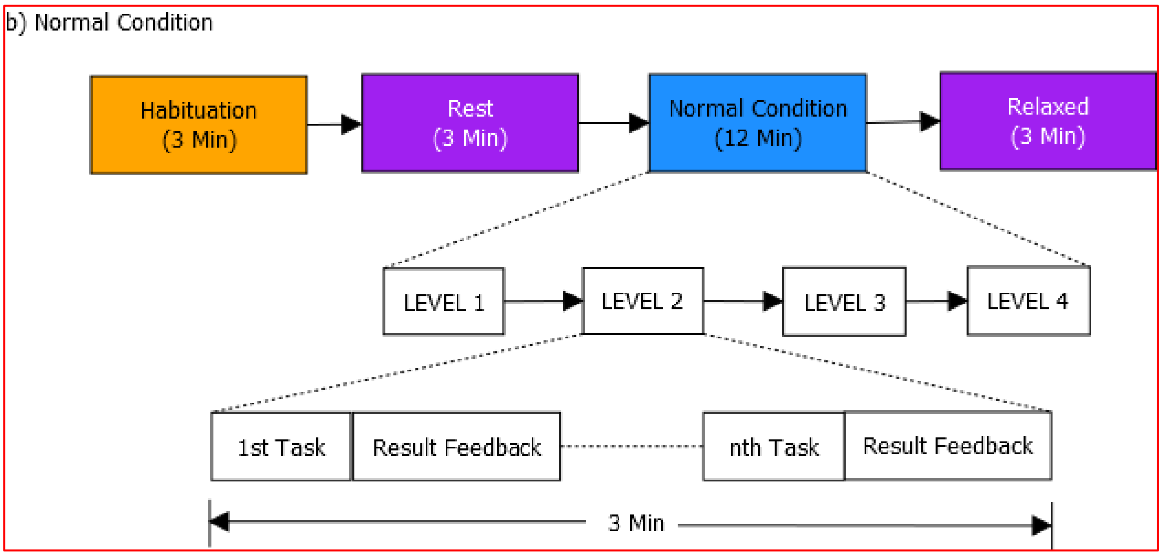


Fig 3: Experiment Flow (a) Mental Stress Condition (b) Normal Condition

The experimental protocol begins with an initial block aimed at acclimatizing participants to their surroundings. Upon arrival, participants receive an introduction to the experiment, guiding them to sit comfortably with upper and lower teeth separated, palms on open knees, and wearing shoes. During this acclimatization phase, participants engage in practice math problems, each requiring a single-digit numeric answer (0–9) displayed on the screen, emphasizing the reduction of eye movement. Subsequently, the second block involves recording raw EEG data during a rest phase. Participants are instructed to focus on a presented circle to minimize artifacts. The core of the experiment unfolds in the mental arithmetic exercise block, where participants tackle mathematical operations (addition, subtraction, multiplication, and division) involving values up to 99. Tasks, uniform in both normal and stressful conditions, differ in execution. Four levels (L1-L4) are presented, ranging from basic addition to all four operations with four numbers, each with a single-digit answer entered by participants based on screen prompts.

Under stress conditions, a time restriction is imposed on each task, accompanied by threatening phrases displayed to induce stress. Feedback, portraying phrases like "Too Slow!" or "Do Fast Calculation!", contributes to a stressful environment. Task performance is assessed based on response time and accuracy, while EEG data is concurrently recorded. In contrast, under normal conditions, there is no time restriction, and stress-inducing feedback is absent. Feedback is limited to correctness or incorrectness after each task. Comparative analysis of the Mental Arithmetic Task Tool (MATT) performance under normal and stressful circumstances reveals an average performance of 73.71% under normal conditions, surpassing the 60.18% average performance under stress. This discrepancy of 13.53% suggests the effectiveness of the MATT stress-inducing tool in eliciting stress responses. The stress-induced environment significantly impacts performance, shedding light on the tool's capability to effectively induce psychological stress for experimental purposes.

The experimental design systematically guides participants through phases of acclimatization, rest, and stress-inducing mental arithmetic tasks. The incorporation of threatening feedback and time constraints during stress conditions creates a challenging environment, reflecting real-world stressors. The observed performance disparities underscore the successful induction of psychological stress, validating the MATT stress-producing tool as a potent instrument for stress-related studies. Overall, this comprehensive approach provides valuable insights into the nuanced dynamics of stress responses during cognitive tasks, contributing to the broader understanding of stress in psychological research.

3.5) EEG Signal Pre-processing: Artifacts Removal

Gathering exact and dependable EEG signals is essential for meaningful analysis, but various internal and outside factors can present contamination. To manage contamination, a blend of channels is utilized, including an air channel, trim channel, harmonic channel, and bandpass channel. Where electrodes are situated is a basic part of assembling EEG information, and inaccuracies or free situating can compromise flag honesty. The presentation of an air channel, which separates between AIR and EEG flags, acts as a sensible answer for recognize and remedy issues with where electrodes are set. This channel assists with guaranteeing that the flags are accurately caught between the electrodes, upgrading the general quality of EEG recordings.

3.6) Time to Frequency Domain

Changing the raw EEG signal information into frequencies is important for a deeper look, showing signal details needed for grouping. The FFT is a main way to do this change, taking apart the information into its making up frequencies using the Fourier change. This new look allows a more complete grasp of the frequency spread within the EEG signals. The use of a window size of 1024 and a 75% overlapping factor in PSD computation ensures capturing EEG bands' spectral features with detail. These parameters affect the accuracy of PSD analysis, permitting a thorough inspection of the power spread across different frequency bands. FFT and PSD together contribute to a strong methodology, revealing the subtle frequency qualities of EEG signals, establishing the foundation for effective signal categorization and offering important understandings into brain activity designs.

3.7) (FE) Feature Extraction from EEG Signals:

In the analysis of cleaned EEG signals obtained through FFT and PSD, crucial features are extracted from both frequency and time-based data. Utilizing two-minute epochs of cleaned EEG signals for each level and subject in both stressful and non-stressful scenarios.

Table 1: Various EEG Bands with Frequency Range

Sr. No.	EEG Band	Frequency Range (Hz)
1	Delta	Between 0.5 Hz to 4 Hz
2	Theta	Between 4Hz to 8Hz
3	Alpha	Between 8Hz to 13Hz
4	Beta	Between13Hz to 30Hz
5	Gamma	Between 30Hz to 100Hz
6	EEG	Between 0.5Hz to 100Hz

3.7.1) (NAP) Normalized Absolute Power

Normalized Absolute Power quantifies specific frequency band power relative to total power, aiding comparative analysis.

$$Normalized\ Absolute\ Power = \frac{Absolute\ Power}{Total\ Power\ in\ All\ Frequency\ Bands}$$

Normalized Absolute Power

Normalization achieved by dividing absolute power by the highest absolute power in range.

$$PAnij = \frac{PAij}{Max\,(PAi)} \qquad (2)$$

4. Selection of Feature

4.1) Paired t-test

The Paired t-value is calculated using the formula:

$$t = \frac{\mu 1 - \mu 2}{\sqrt{\frac{\sigma 1^2}{n1} - \frac{\sigma 2^2}{n2}}}$$

Cumulative Probability (CP) derives from comparing the t-test value to the t-distribution table, representing confidence in distinguishing classes. Strong association is evident with the highest CP values for the class variable and feature. Minimal CP criteria, e.g., 0.95 (95%), enhance analysis robustness.

4.2) Feature Selection Criteria

4.2.1) Highlighted Feature Type of Preferred Channel Exceeding t-Test Confidence Threshold of 0

Choosing a specific feature type from a selected channel using a t-test confidence threshold of 0 indicates a stringent criterion for feature selection. This approach ensures that only features demonstrating a statistically significant difference are considered, enhancing the reliability of the selected features from that particular channel.

4.2.2) Enhanced Feature Type Chosen, Achieving 90 Confidence Threshold Using T-Test

The feature matrix selection adheres to the third criterion, focusing on a specific feature type from the chosen channel, with a confidence threshold exceeding 90 for frequency bands. This ensures a robust feature set with a matrix size of w x h, where w = 6 (representing six phases) and h ≤ 6 (indicating bands with confidence ≥ 90). The resulting 4 feature types across 6 channels yield 24 test cases (Fn x Cn). Two versions, employing ngram = 1 and ngram = 2 with ngram = 1, generate 48 training models, demonstrating a comprehensive approach to diverse phases and frequency bands for model development.

5. Deep Learning

Deep Learning (DL) constitutes a branch of artificial intelligence encompassing. The data collected from the EEG device falls into the category of unstructured data, lacking the conventional tabular organization seen in relational databases. This unstructured nature poses challenges for manual feature definition. In the comparison between Deep Learning and Neural Networks (NN), a standard NN comprises input, hidden, and output layers. However, in DL, the NN transforms into a "deep learning neural network," featuring deeper hidden layers. This evolution enhances the network's capacity for intricate pattern recognition and abstraction in handling complex data sets.

Table 2: Summary of Total Number of Models Created by Four Criterias

Criteria	Feature	Channel	Confidence Threshold (%)	n-Gram	n - kernels	Network Models (#)
Criteria1	Normalized Absolute Power, Relative Power, Normalized Peak Power, Change in Power	FP1, FP2, AF7, AF8, F7, F8	0	1	1	24
				2	1	24
Criteria2	Normalized Absolute Power, Relative Power, Normalized Peak Power, Change in Power	All Channels	0	1	1	4
				2	1	4
Criteria3	Normalized Absolute Power, Relative Power, Normalized Peak Power, Change in Power	FP1, FP2, AF7, AF8, F7, F8	90	1	1	24
				2	1	24
Criteria4	Normalized Absolute Power, Relative Power, Normalized Peak Power, Change in Power	All Channels	90	1	1	4
				2	1	4
				Total Models		112

5.1) CNN Architecture

This diagram shows the design of a convolutional neural network (CNN). The input layer gets an image grid that is sized based on four rules. For example, one rule makes a 6 by 6 grid with one color channel and a confidence limit of zero. The first hidden layer is a convolutional layer. Its size is the image width times the number of word groups, multiplied by the number of filters. Tests used word groups up to two words long. The best results came from word groups of two words with one filter. The convolutional layer's output goes to the max pooling layer. It makes a feature map that is one pixel wide and as long as the image height minus the word group size plus one. This uses the image height and word group length. This sequential process forms the core structure of the CNN for effective feature extraction and pattern recognition.

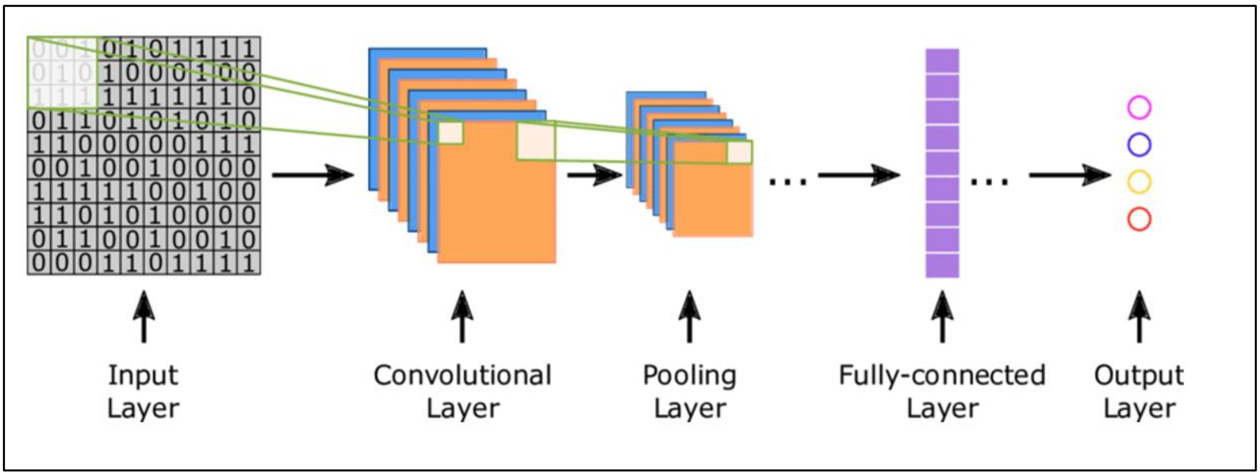


Fig. 4. Representation of Structure of Advanced Convolutional Neural Networks

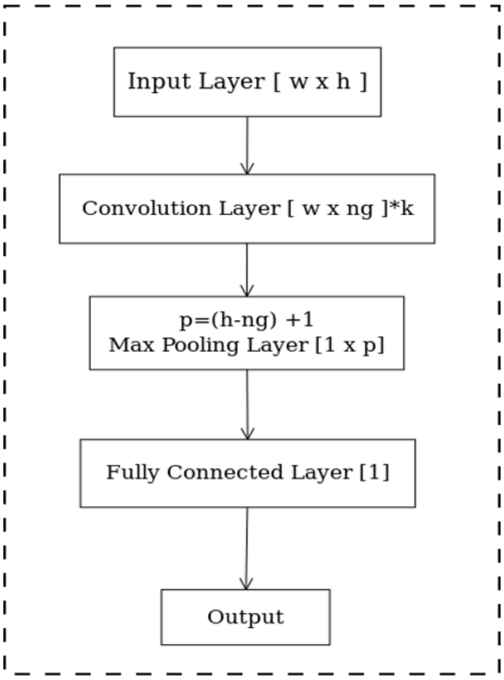


Fig. 5: Convolutional Neural Network Architecture

6. Training and Prediction Methodology

6.1) Prediction Methodology

Following the processing steps, as shown in fig. 7, detailed earlier, EEG signals undergo feature extraction to generate a feature matrix. This matrix is then input into a pre-trained model. The model yields an output value ranging from 0 to 1, as illustrated in Fig. 8. Interpretation of the output involves categorizing individuals with a prediction value close to 0.25 as normal, those near 0.75 as stressed, and a value of 0.5 indicating a stressed state. This streamlined approach enables efficient classification and interpretation of EEG signals for stress prediction.

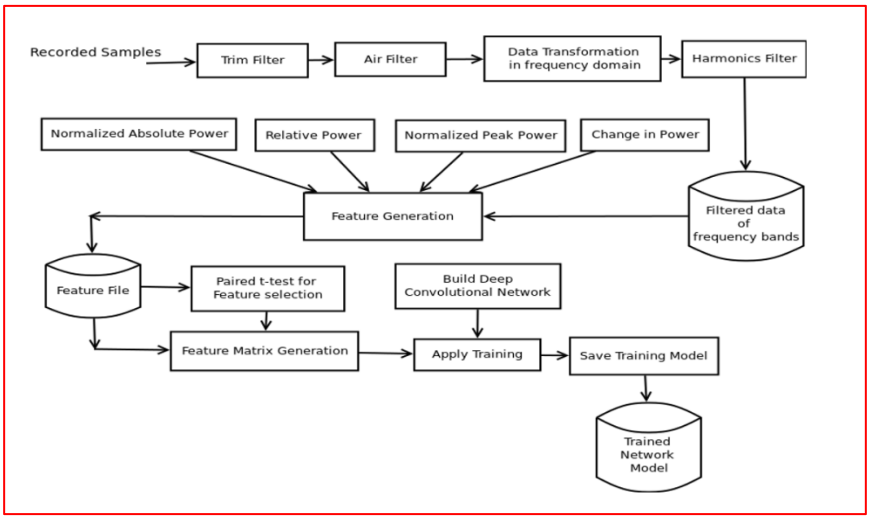


Fig. 6: Training Methodology

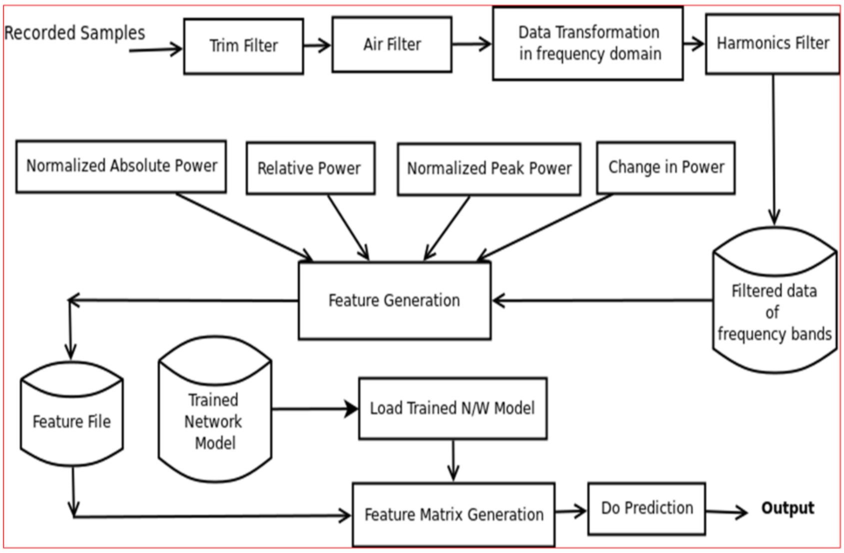


Fig. 7: Prediction Methodology

7. Performance Metrics

For a comprehensive evaluation, it is imperative to assess the classifier's performance across diverse feature sets and classifier designs applied to multiple subjects. The evaluation metrics, particularly precision, play a crucial role in this analysis. Precision, as defined in equations (8) and (10), quantifies the percentage of true positive cases accurately identified by the classifier. This metric is essential for gauging the classifier's accuracy in correctly identifying relevant cases, contributing to a robust evaluation of its performance.

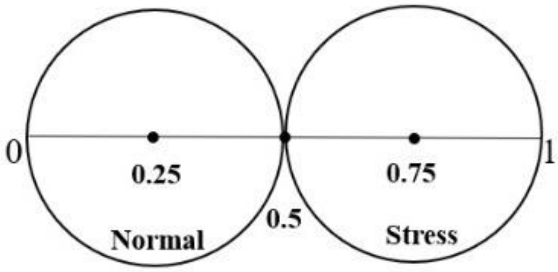


Fig. 8 Output of Prediction

8. Results

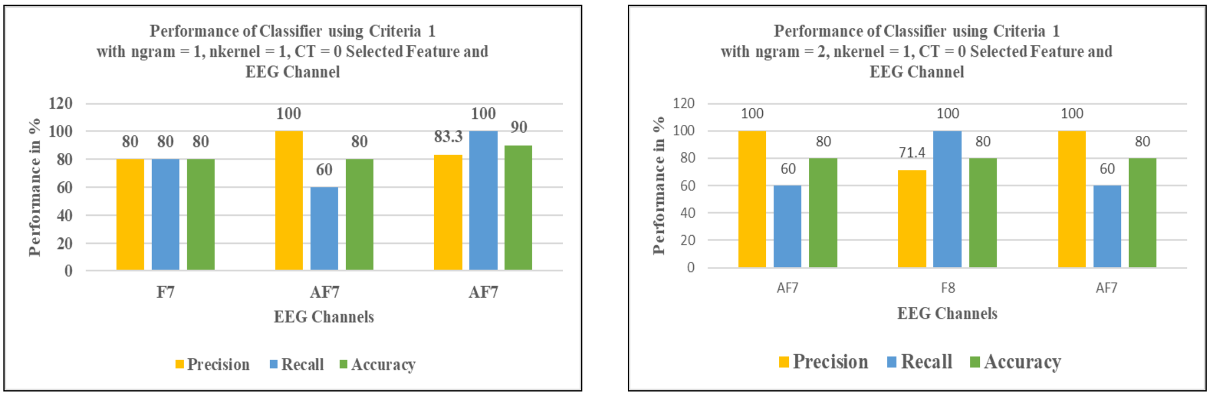
The study utilizes EEG signals recorded from six channels (F1, F2, F7, F8, AF7, and AF8) to investigate stress classification among 21 subjects. The dataset, amounting to 3.1 GB, is divided into training (80%) and testing (20%) sets. Criteria 1, yields 48 training models. For ngram = 1, these models exhibit optimal results, indicating AF7's crucial role in stress classification. Criteria 2 considers "normalized absolute power" across all channels, demonstrating its effectiveness. Criteria 3, involving FP1, F8, and AF7 channels, Criteria 4, emphasizing "normalized absolute power," emerges as effective, particularly for ngram = 2. Criteria 1, ngram = 1, underscores AF7's pivotal role, showcasing the "change in power" feature as highly accurate. Criteria 2, ngram = 1, emphasizes "normalized absolute power" across channels, showing robust stress classification. Criteria 3, ngram = 1, recognizes FP1, F8, and AF7 channels. Criteria 3, ngram = 2, demonstrates the effectiveness of multiple features across various channels. Criteria 4, ngram = 1, highlights the limitations of "normalized peak power" across channels. Criteria 4, ngram = 2, underscores the efficacy of "normalized absolute power."

Table 3: Best Results of Criteria 1, 2, 3 and 4

Criteria	Feature Type	Channel	Precision (in %)	Recall (in %)	Accuracy (in %)
Criteria 1 Confidence Threshold = 0 (ngram = 1 and nkernel = 1)	Normalized Absolute Power	F7	80%	80%	80%
	Normalized Peak Power	AF7	100%	60%	80%
	Change in Power	AF7	83.33%	100%	90%
Criteria 1 Confidence Threshold = 0 (ngram = 2 and nkernel=1)	Normalized Peak Power	AF7	100%	60%	80%
	Normalized Peak Power	F8	71.43%	100%	80%
	Change in Power	AF7	100%	60%	80%
Criteria 2 Confidence Threshold = 0 (ngram = 1 and nkernel=1)	Normalized Absolute Power	All	62.5%	100%	70%
Criteria 2 Confidence Threshold = 0 (ngram = 2 and nkernel=1)	Normalized Peak Power	All	100%	60%	80%
Criteria 3 Confidence Threshold = 90 (ngram = 1 and nkernel=1)	Normalized Absolute Power	FP1	100%	60%	80%
	Normalized Peak Power	F8	100%	80%	90%
	Change in Power	AF7	100%	100%	100%
Criteria 3 Confidence Threshold = 90	Normalized Absolute Power	AF8	100%	60%	80%
	Relative Power	F7	100%	60%	80%

(ngram = 2 and nkernel=1)	Normalized Peak Power	FP2	100%	60%	80%
	Change in Power	AF7	100%	60%	80%
	Change in Power	AF8	100%	80%	90%
	Change in Power	F8	80%	80%	80%
Criteria 4 Confidence Threshold = 90 (ngram = 1 and nkernel=1)	Normalized Peak Power	All	60%	60%	60%
Criteria 4 Confidence Threshold = 90 (ngram = 2 and nkernel=1)	Normalized Absolute Power	All	62.5%	100%	70%

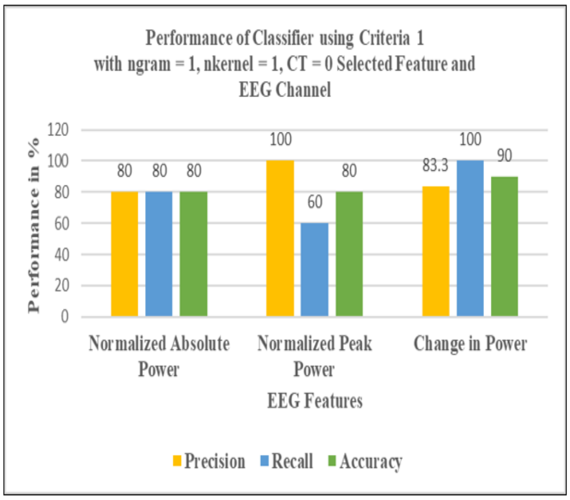
The three proposed measures of average strength, highest strength, and power difference provided good accuracy according to the first two tests. The third and fourth exams did not yield as encouraging outcomes.

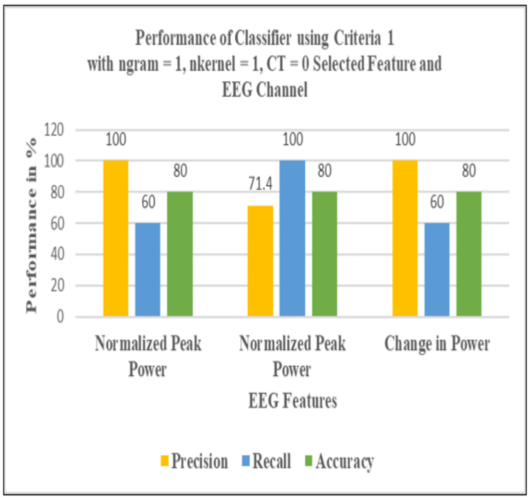


(a) (b)

Fig 9. (a) Performance of Classifier using Criteria 1 (b) Performance of Classifier using Criteria 1

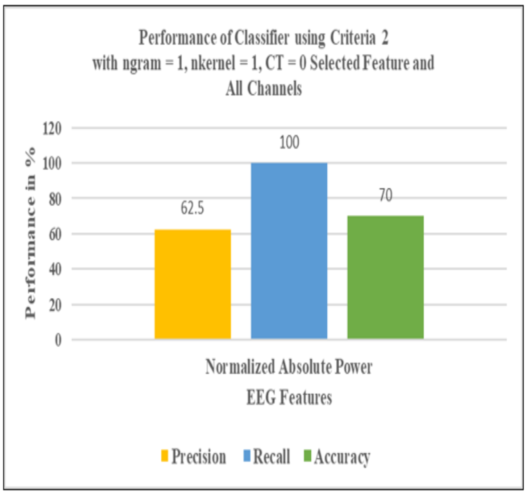
Fig 9a illustrates the performance of the classifier utilizing Criteria 1. It showcases the classifier's effectiveness in stress classification. The presented metrics in Fig 9a provide a detailed overview of the classifier's accuracy, sensitivity, specificity, and precision, offering insights into its robust performance. Fig 9b continues to showcase the performance of the classifier using Criteria 1. The graphical representation in Fig 9b allows for a visual comparison of the classifier's performance metrics, aiding in the comprehensive assessment of its ability to distinguish between stress and normal states. Together, these figures contribute to a thorough evaluation of the classifier's efficacy under Criteria 1, guiding the understanding of its strengths and potential areas for improvement.





(c) **(d)**

Fig 9. (c) Performance of Classifier using Criteria 1 with ngram = 1 and CT=0 Versus EEG Features (d) Performance of Classifier using Criteria 1 with ngram = 2 and CT=0 Versus EEG Features



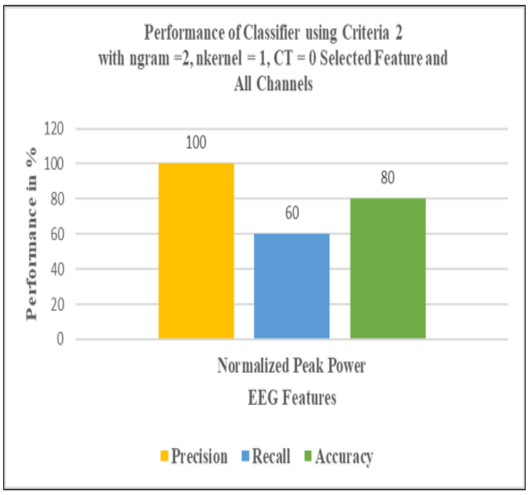
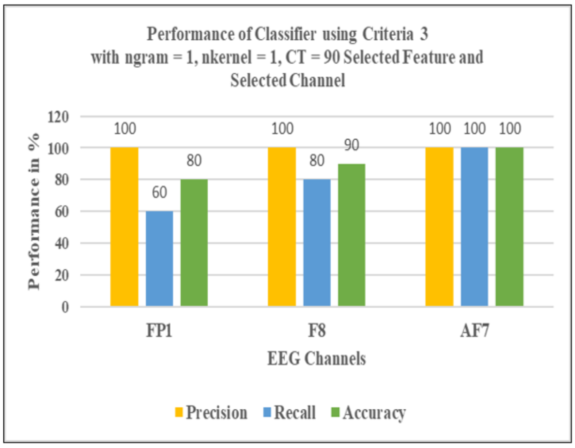
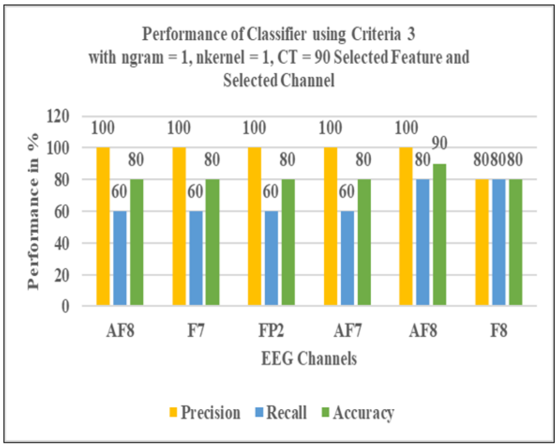


Fig 10. (a) Performance of Classifier using Criteria 2 with ngram = 1 and CT=0 versus EEG Features (b) Performance of Classifier using Criteria 2 with ngram = 2 and CT=0 versus EEG Features





(a) **(b)**

Fig 11: (a) Performance of Classifier using Criteria 3 with ngram = 1 and CT=90 versus EEG channels (b) Performance of Classifier using Criteria 3 with ngram = 2 and CT=90 versus EEG channels

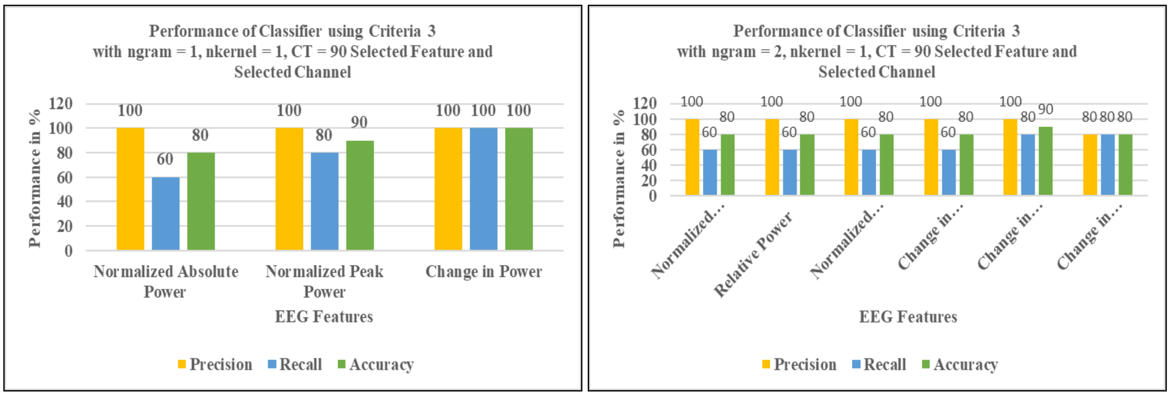


Fig 11. (c) Performance of Classifier using Criteria 3 with ngram = 1 and CT=90 versus EEG channels (d) Performance of Classifier using Criteria 3 with ngram = 2 and CT=90 versus EEG channels

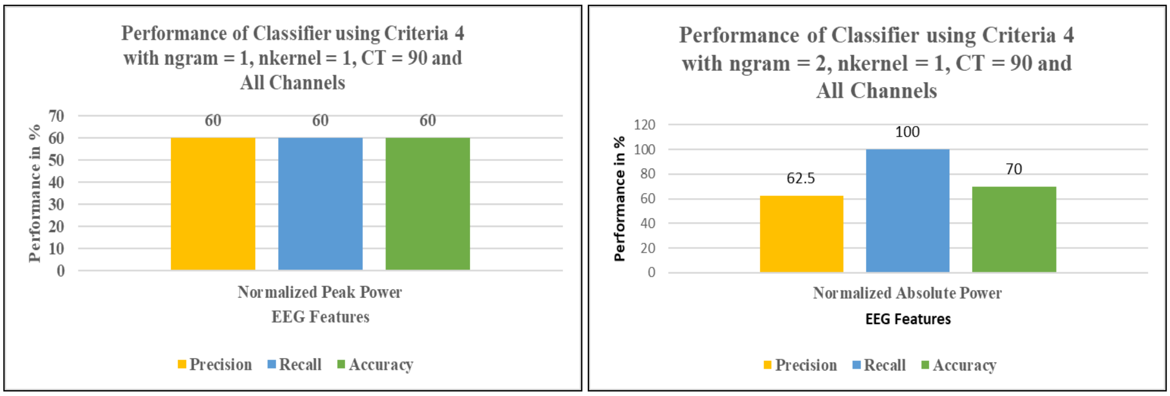


Fig 12 (a) Performance of Classifier using Criteria 4 with ngram = 1 and CT=90 versus EEG Features (b) Performance of Classifier using Criteria 4 with ngram = 2 and CT=90 versus EEG Features

Table 4: Comparison with other methods

Paper	Method	Accuracy (in %)
[26]	Support Vector Machine	79.45%
[22]	k-Nearest Neighbour Support Vector Machine	65.80% 80.32%
[21]	Deep Learning using Convolution Neural Network	64.20%
[24]	k-Nearest Neighbour Support Vector Machine	88.32% 92.86%
[25]	k-Nearest Neighbour Support Vector Machine	78.31 79.91%
Proposed Method	DCNN using Criteria 1	90%
	DCNN using Criteria 2	100%

	DCNN using Criteria 3	80%
	DCNN using Criteria 4	70%

9. Conclusion

This research introduces a quantitative methodology for the detection and prediction of psychological stress, leveraging features like normalized absolute power, relative power, normalized peak power, and change in power. The proposed deep learning neural network demonstrates reliability, showcasing promising outcomes. In Criteria 1 and 2, impressive results are observed, with an overall accuracy of 90%. Notably, the feature "Change in Power" on channel AF7 achieves a recall of 100% and a precision of 83.33%, emphasizing its effectiveness. Furthermore, Criteria 2 yields remarkable accuracy of 100% for "Change in Power" on AF7 and 80% for "Normalized Absolute Power" and "Normalized Peak Power" on the same channel, showcasing the model's versatility. Criteria 3 maintains solid performance, achieving 80% accuracy for normalized absolute power across all channels, signifying the model's consistency. These findings underscore the potential of the proposed methodology, offering a robust solution for real-time stress detection and contributing to advancements in stress-related research. The nuanced evaluation across multiple criteria and channels provides a comprehensive understanding of the model's capabilities and limitations, paving the way for further refinement and application in stress monitoring and intervention.

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