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# Comprehensive Review on Stress Detection using EEG Signals and Machine Learning Techniques.

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***Abstract: -*** Stress significantly impacts mental and physical health, making accurate detection essential for enhancing productivity and well-being. Electroencephalography (EEG) has emerged as a pivotal tool for stress analysis, offering a non-invasive, cost-effective, and temporally precise method to evaluate brain activity. This paper reviews advancements in stress detection using machine learning (ML) and deep learning (DL) techniques applied to EEG data. Traditional stress detection methods, such as self-reports and subjective surveys, face limitations in reliability and scalability. In contrast, ML and DL models, including Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNNs), and hybrid architectures, demonstrate superior feature extraction and classification accuracy. Studies have reported classification accuracies exceeding 95% using advanced signal processing and hybrid frameworks. However, challenges remain in optimizing computational efficiency, reducing algorithmic complexity, and validating models on diverse, real-time datasets. This review highlights the potential of innovative feature extraction techniques and hybrid ML-DL models to address these gaps, paving the way for robust, scalable, and real-time stress detection systems. By overcoming current limitations, future research can significantly contribute to mental health management and preventive care strategies. This paper provides a comprehensive overview of recent advancements and outlines future directions in EEG-based stress detection research.

***Keywords:*** Stress Detection, EEG, Machine Learning, Deep Learning, Feature Extraction.

## I. INTRODUCTION

Stress, a multifaceted response to emotional, physical, or mental challenges, has become an endemic concern in today's fast-paced world. While moderate stress (eustress) can enhance focus and performance, chronic or excessive stress (distress) can lead to severe mental health issues, such as depression and anxiety, impairing productivity and quality of life. The recognition and measurement of stress are thus critical for early intervention and effective management. Traditional methods for stress assessment rely heavily on self-reports, surveys, and psychometric scales. These approaches, though widely used, are inherently subjective and prone to inaccuracies. Consequently, there has been growing interest in leveraging physiological signals as more objective markers of stress. Among these, electroencephalography (EEG) has emerged as a preferred modality due to its high temporal resolution, affordability, and user-friendliness. EEG captures brain activity in the form of electrical signals, which can be analyzed to discern stress-related patterns. Recent advances in machine learning (ML) and deep learning (DL) have revolutionized EEG-based stress detection. These techniques enable automated feature extraction and classification, overcoming the limitations of traditional feature engineering. Studies employing models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid frameworks have demonstrated significant improvements in accuracy and robustness. For instance, hybrid deep learning architectures combining Long Short-Term Memory (LSTM) and wavelet transforms have achieved classification accuracies exceeding 95% in stress detection tasks. When your body's emotional response to things like despair, worry, rage, grief, guilt, low self-esteem, etc., shifts, you may experience stress. Stress can be either beneficial (eustress) or harmful (distress) [1]. Mental health issues like depression and dementia can have their origins in stress, which also hurts a person's productivity [2]. Since stress-related problems are growing given the exponential growth of stress globally, the recognition and measurement of stress have become immensely crucial [3]. Stress can be evaluated in various ways. Self-reports have been the sole reliable source for measuring stress[4]. Subjects can fill out conventional questionnaires, and their responses will be mapped to predetermined scales. A total score is determined by adding up the points earned from correct answers to each question [5]. However, since the identification of stress is dependent on the questionnaire, this approach is not accurate. Hence, we require a system capable of autonomously categorizing individuals into stress and non-stress groups. Furthermore, this may also be advantageous for preventive measures, such as increasing public consciousness regarding mental health [6]. Surveys, facial languages (wink amount, speech field, etc.), social media posts, and other such methods of

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gauging stress are either subjective or difficult to evaluate [7]. Numerous physiological measures, including skin conductance, blood pressure, and brain activity, have been demonstrated to be significantly affected by stress [8]. (EEG),(fMRI), and (PET) were all utilized for stress discovery[9]. Physical, physiological, and other characteristics can be used to differentiate between stressed and non-stressed people. But there is no single way to quantify stress. Classifications were established with a wide variety of attributes in several distinct tries. Yet results vary depending on the feature set used. Due to its ability to handle raw data directly, deep learning may automatically identify the most significant features without the need for feature engineering or pre-processing [10], [11], Moreover, it has newly acquired widespread use in the domain of stress detection utilizing EEG [12]. Although deep neural networks can be trained to recognize features, prior feature extraction improves performance, as shown in [13]. Also, the deep learning model requires a lot of information. This highlights the importance of developing a stress detection system that uses an advanced feature extraction method. However, it is not easy to determine which traits are most useful for stress classification. In addition, the variety and quantity of features to be retrieved vary greatly across headband types. Key benefits of EEG include its affordability, excellent temporal resolution, and user-friendly interface. Stress and other mental states can be evaluated using this method, which is one of the most common ones [14], [15]. Various academics have conducted extensive studies on the topic of stress management utilizing EEG signals. However, upon conducting the literature research, we discovered that there is still room for enhancement in this area. We have identified the following main constraints.

1. Lack of better analytical detection algorithm and lack of full leverage of ML and DL algorithms
2. The bulk of the studies were conducted using a single EEG dataset. No hybrid dataset was employed.
3. The primary constraint of Deep Learning (DL) algorithms is their time complexity, which arises from the extensive integration of methods. The intricacy of the proposed model significantly inhibits the assessment of its accuracy on the EEG Dataset.
4. An inherent constraint of deep learning-based hybrid models is their complexity resulting from extensive parameter adjustment, which necessitates longer execution times.
5. Minimizing the parameter count of hybrid algorithm combinations is necessary to enable their execution on edge devices.
6. Insufficient model dimensions in the dataset and the need to enhance the quality of chosen samples. Also, the proposed model lacks the validation of their algorithms on real-time datasets.

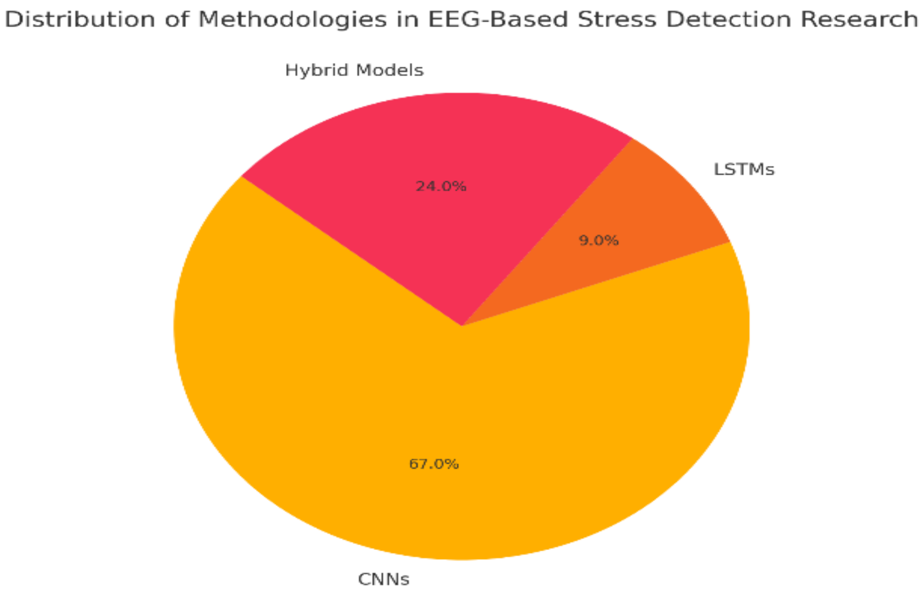


**Figure 1: Pie Chart showing Methodologies Distribution**

The pie chart shown in figure 1 illustrates the distribution of methodologies used in EEG-based stress detection research. It highlights that Convolutional Neural Networks (CNNs) dominate the field, accounting for 67% of the approaches. This preference stems from their efficiency in feature extraction and classification tasks.

Hybrid models, which combine multiple deep learning techniques for enhanced performance, constitute 24% of the methodologies, showcasing their importance in improving classification accuracy and robustness. Long Short-Term Memory networks (LSTMs), known for handling sequential data and temporal dependencies, are utilized in 9% of studies. This distribution underscores the prominence of CNNs in EEG-based stress detection while emphasizing the growing interest in hybrid approaches and the specialized role of LSTMs in this research domain.

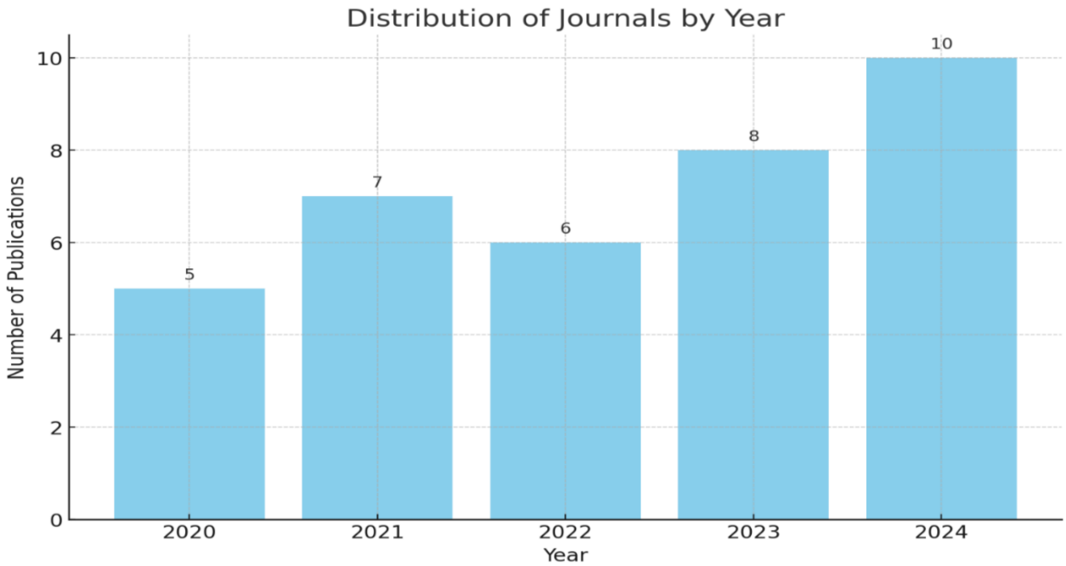


**Figure 2: Distribution of Papers Year Wise**

The bar chart in figure 2 depicts the annual distribution of journal publications related to EEG-based stress detection research over a five-year period. There is a noticeable upward trend, indicating growing interest and advancements in the field. In 2020, only 5 publications were recorded, but this number steadily increased to 10 by 2024. This progression reflects the expanding focus on stress detection methodologies, particularly leveraging machine learning and deep learning techniques, as researchers address the increasing need for effective mental health management tools. The consistent rise in publications underscores the evolving importance and recognition of this research domain.

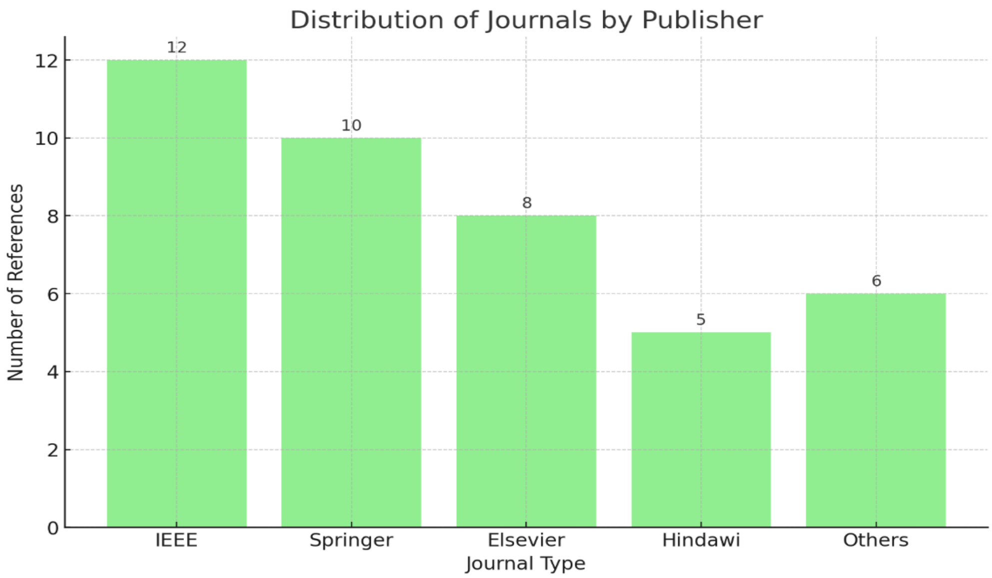


***Figure 3: Distribution of articles Publication Wise***

The bar chart in figure 3 displays the distribution of journal references categorized by publisher types. IEEE emerges as the leading publisher, contributing the highest number of references (12), reflecting its dominance in technical and engineering research. Springer follows with 10 references, showcasing its significant role in academic publishing. Elsevier is next with 8 references, emphasizing its contribution to multidisciplinary research. Hindawi accounts for 5 references, highlighting its presence in open-access publishing. Lastly, other publishers collectively contribute 6 references, showcasing the diversity in sources. This distribution underscores the reliance on major academic publishers for authoritative and high-impact research in the domain. However, challenges persist. The high computational complexity of deep learning models, the variability of EEG signal characteristics across individuals, and the lack of diverse datasets hinder the generalizability and real-world applicability of these systems. Moreover, real-time stress detection demands lightweight and efficient models suitable for deployment on edge devices. This paper reviews the current state of EEG-based stress detection, focusing on methodologies, challenges, and future prospects. By identifying gaps in existing research, we aim to provide a roadmap for developing robust and scalable solutions for stress detection and management.

## II. LITERATURE REVIEW

In recent years, many methodologies for categorizing psychological stress based on EEG signals using different techniques have been developed. Some of the recent and important literature is reviewed in this section. Empirical EEG is a highly efficient non-invasive instrument extensively employed in both clinical and research domains, this work proposes a comparative analysis of PET, ECG, EMG, and MRI techniques of stress identification and emphasizes a stress detection approach utilizing EEG signals. Three FD techniques, Utilization of Higuchi, Katz, and Permutation Entropy in stress detection for extracting features has been seen. FD serves as an indicator of curve anomalies. The purpose of this research done by Agrawal et al. was to apply and compare many traditional machine-learning classification methods in terms of their correctness, exactness, and sensitivity. Using MATLAB for EEG analysis, fractal dimension for feature withdrawal, and ML processes (A study of RF and ANN) for classification were implemented. This proposed work presents a novel architecture that can be used to detect stress early on, classify it into three levels (minor, reasonable, and tall), and teach people how to deal with stress so that it doesn't get in the way of their productivity.[16]

This work introduced by Gupta R, et al was the combination of five methods to improve the precision of EEG stress detection. This study utilizes an advanced version of the Whale Optimization Algorithm to choose the optimal kernel for stress prediction in the Support Vector Machine classifier. The present work employed an extensive array of algorithms, namely NLM, DCT, and MBPSO, to carry out data pre-processing, feature extraction, and feature selection. This study involved an empirical assessment of the suggested stress detection method using 14 sets of EEG data. In terms of statistical correctness (96.36%), sensitivity (96.84%), specificity (90.88%), and F1 score (97.96%), the proposed strategy outperformed the most technologically sophisticated methods [9].

A comparison analysis was performed on epoch data acquired from channels of EEG sensors. The dimensionality reduction was achieved using several machine learning techniques, Encompassing SVM, KNN, LR, LDA and DT. This work integrated both methodologies with and without the use of (PCA). All machine hyper-parameters were optimized using a grid search approach. learning models assessed on the Spark cluster, to further decrease execution time. In this study, the present work employed the Multimodal Dataset for the Analysis of Human Affective States, often known as the DEAP Dataset. Participants classified 40 different 1-minute musical snippets, and their designations served as the basis for the subsequent predictions. The participants gave each film a rating based on how arousing, uplifting, dominating, and familiar it made them feel. The data from each epoch was partitioned into 15-second intervals, and the binary classifiers were trained using these intervals. Optimized results were obtained by using (PCA) with (SVM), yielding an F1-score of 84.73% and a recall of 98.01% for the segmentation timeframe of 30–45 minutes [17].

Sharma R. and Chopra K. provided the results from an examination of stress using brain signals. For forensic purposes, EEG signals were very accurate, precise, and trustworthy. Using this method, the author found that increased anxiety, perspiration, and body temperature were the most disruptive factors. However, EEG is very congruent with other stress signals. The author conducted a comprehensive comparison of available classifiers and found that SVM yielded the highest accuracy. Results of this study enabled the implementation of clinical intervention and The viability of employing EEG for stress detection is proven in the mitigation of stress-induced bodily and mental health pathologies [18].

Saeed S. Anwar et al classified human long-term stress based on EEG data using two distinct labelling strategies. In this study, they aimed at classifying chronic stress based on 45 signal components, alpha asymmetry emerged as a significant differentiator when expert judgement was used as the gold standard. When used in isolation for labelling, the PSS ratings provided no meaningful characteristics. The empirical methods shown that SVM and LR attain the maximum accuracy of 85.20% for classification jobs. Furthermore, the author observed that the stress group exhibited superior categorization compared to the control group across all available classifiers. Ultimately, it was shown that alpha asymmetry has potential as a biomarker for the machine learning-based classification of chronic stress [19].

An EEG-based stress monitoring system for the working population is proposed using this technology. The incidence of stress is fairly prevalent. Many medical ailments are the direct result of stress. The EEG is a valid method of stress assessment. To get at the meat of the EEG, the author performed temporal frequency analysis. Under pressure, respondents' alpha waves only register an accuracy of 90.32 per cent [12].

An EEG-based stress categorization system is proposed in this research. Digital EEG signals from 35 participants were captured and recorded Operationalizing a commercially accessible Muse EEG helmet equipped with four electrode, and the resulting data were analyzed.To induce tension, P.N.Relan D. et.al selected four scenes from different films. Two videos were chosen for their potential to create stress due to their inclusion of emotionally charged moments. Because of the abundance of comedic moments, the other two videos were selected. Stress was categorised based on the signals that were captured. To categorize the stress and non-stress groups, the author performed a performance evaluation of the (MLP) and (LSTM) models. The two-layer LSTM architecture achieved the highest overall classification accuracy of 93.17 percent [20].

Turk O. et al. offered a method for automatically classifying EEG data without resorting to at all pre-processing techniques like changes (Fourier transform, wavelet transform, etc.) or feature abstraction. The SEED EEG dataset, which includes positive, negative, and neutral emotional states, was employed with (CNNs) as classifiers to achieve this goal. Fifteen people were interviewed throughout three sessions, and their data was used. The suggested method converts raw channel-time EEG recordings into unitary pattern segments of size 28 by 28 without any additional intervention.In the following stage, CNN categorises the collected patterns. After sorting, the overall average performance across all participants on the three emotions was determined to be 88.84%. Classification performances range from a high of 93.91 per cent among participants to a low of 77.70 per cent. Furthermore, the average f-scores for good emotion, negative emotion, and neutral mood are all 0.88[10].

S.A. Tomar et.al introduced a LSTM network designed for the purpose of emotion identification using EEG data. The main objective of this method was to evaluate the classification performance of the LSTM model.Examination of the behaviour of individuals of different age groups and genders was a secondary aim. In the context of classification, the author assessed the efficacy of deep learning models based on MLP, KNN, SVM, LIB-SVM, and LSTM. The findings from 50-50, 60-40, 70-30, and 10-fold cross-validation indicate that the deep learning model based on LSTM achieves classification accuracy of 83.12%, 86.94%, 91.67%, and 94.12% for four different emotion categories, respectively. For three emotion categories, an LSTM-based deep learning model achieved classification accuracies of 81.33%, 85.41%, 89.44%, and 92.66%. These accuracies were calculated using 50-50, 60-40, 70-30, and 10-fold cross-validation method, respectively [21].

Heimer A. et al. Presented a comprehensive stress dataset that include online job interviews as a unique stressor. The collection comprised audial, audiovisual (including sign capture, facial recognition, and eye tracking) and physiological data such as PPG and EEG from in excess of 40 persons.Time-continuous annotations for stress and experienced emotions (including humiliation, rage, anxiety, and surprise) were also included in the dataset. A binary stress classification problem was addressed using the proposed dataset to train and evaluate five distinct ML classifiers: Among machine learning techniques include SVM,KNN,RF,LSTM networks. The highest accuracy and F1-score that any classifier managed to obtain was 88.3% and 87.5%, respectively. Affective computing, job interviews, digital stress, stress physiology, and stress dataset are some of the terms used in the index[22].

Chen et.al developed a battery of programs to gather data and subject it to artificial stress. Research undertaken by 80 W. Chen et al. identified the Kraepelin test, the Stroop test, and its modifications as potential sources of stress-induced activation. Data from 120 people' face movements, PPG, and EDA were obtained. The obtained data is analyzed to validate the association between physiological markers and applied pressure in order to

benchmark machine learning approaches for stress detection. They also outperformed the standard for basic neural network models in stress detection [23].
A study conducted by Kaminska D. examined the practicality of utilizing EEG signals for the purpose of categorizing a user's stress levels within a virtual reality setting. In order to do this, the author utilized the Exploring the Stroop test as a stressor and created a virtual reality (VR) interactive simulation that included soothing sequences derived from psychotherapy treatment integrating bilateral stimulation. Twenty-eight healthy adult volunteers had their EEG signals tracked in real time using the EMOTIV EPOC Flex wireless EEG head cap device. Conventional machine learning techniques, including CNN, were subsequently employed to classify the stress level.Conversely, the acquired values were enough for use in an MLP classification of the emotions of tension and relaxation. The rate of success in classifying data was more than 90%. The best outcomes were achieved when all brain waves were taken into account (96.42%). Individual study of theta (94.64%), gamma (80.36%), and alpha (76.78%), waves produced the most hopeful findings [24].

EEG lets one continuously monitor brain states including human cognitive activity, emotions, and stress levels because to its extraordinary temporal resolution. The main goal is to assess cognitive stress detecting system efficiency. The current state of stress detection systems lacks adequate availability of suitable EEG channels and effective band selection solutions. R. Suyawanshi and S. Wanjale employed a brain interface including a minimal number of channels to do stress analysis using EEG. In this regard, a Quick FT dimension reduction technique was utilized, which effectively decreased the volume of data originating from the root. Three model taxonomy algorithms were trained using correlation-based feature subset selection techniques and Fourier transform based approaches: (SVM),(KNN), (DT), and (CNN)[25].
N.P. Nikitha et.al propose a MATLAB approach to use EEG analysis, within a ML framework, to detect and identify stress levels. The author(s) examined various techniques with which EEG signals can be analyzed. The operators of Discrete Cosine Transform and Discrete Wave Transform can be employed to acquire these features. The classifiers that have been implemented are NB, ANN, KNN, LDA, and SVM. The outcome was favorable [26].
An implicit-more-controlled EEG paradigm was used by Andrea Apicella et.al to evoke emotional valence in 25 volunteers without depressive illnesses by having them passively observe standardized visual stimuli (specifically, the Oasis dataset). The compatibility of the experimental sample with Oasis has been confirmed by the findings of the Self-Assessment Manikin questionnaire. A comparative analysis was conducted on two distinct approaches for feature extraction: (i) relying on prior knowledge, namely Hemispheric Asymmetry Theories, and (ii) by the use of an automated procedure that combines elements of a common spatial pattern with a proprietary 12-band filter bank. The shallow ANN attained a mean accuracy of 96.1% inside an individual participant, whereas the KNN approach produced a cross-subject accuracy of 80.2% [27].
To investigate the theta, alpha, and beta resonance bands' features related to stress in the frequency domain, M. Wali et al. employed wavelet packet transform to extract electroencephalogram features. The present study involved the provision of four features to an extreme learning machine, resulting in a detection accuracy of 98.56% for stress compared to the normal state. The machine's corresponding specificity is 95.88%, and its average sensitivity is 92.52%. Various cues in a noisy atmosphere were used to investigate the stress experienced by 15 students during mathematical exercises [28].
A thorough approach for extracting characteristics and classifying stress levels was developed by B. Roy et al. using deep learning models such as two layers of a GRU network, BiLSTM, and DWT-based CNN. The non-linear and non-stationary features of multi-channel (14-channel) EEG recordings were eliminated and the data were divided into precise frequency bands using DWT analysis. Automatic feature extraction was performed on the broken-down signals using the (CNN), while the stress levels were classified using BiLSTM and two layers of (GRU). In comparison to the suggested model, this study compares five different configurations of the CNN, LSTM, BiLSTM, GRU, and RNN models. When measured against the other models under investigation, the suggested hybrid model showed a greater classification accuracy. As a result, hybrid combinations are suitable for the treatment of mental and physical illnesses as well as their prevention [29].
The research evaluation conducted by S. Pourmohammadi et al demonstrated that EMG and ECG signals exhibit accurate classification of pressure levels, Accomplishing correctness rates of 100%, 97.6%, and 96.2% for stress levels of 2, 3, and 4 degrees, respectively. Moreover, empirical evidence has shown that the (EMG) signal of the right trapezius muscle displays enhanced capacity for detecting stress in comparison to other muscles.

Cumulatively, these findings imply that, when it came to stress screening, the EMG signal functioned on par with the well-respected ECG signal.

The present study enhances the current understanding of physiological stress detection by offering comprehensive data on the capacity of various muscle EMG signals to identify pressure levels, and subsequently comparing them with the ECG signal [30].

Ali Nirabi et.al introduced a ML approach to identify the physiological stress levels from EEG signals. Using a band-pass (FIR) filter, the recommended methodology first eliminated physiological sounds from the EEG signal. A (DWT) method was used to extract features from the filtered EEG input. An ensemble of classifiers, including (kNN),(SVM), NB, and (LDA), was used to classify the features. Our analysis of two tiers of stressed EEG data yielded classification accuracies of 86.3%, 91.0%, 81.7%, and 90.0%. The SVM classifier outperforms the current state of the art by 15.8% to reach the best classification accuracy [31].

The authors, M. Sheeraz et.al, introduced an innovative wireless wearable system that performs simultaneous measurements of EEG and ECG using a mere three non-invasive electrodes. The devised device features a compact design, characteristic of being lightweight and conveniently worn behind the ear. The device has an exceptionally low power consumption and achieves outstanding noise performance (0.1µVrms) covering a frequency range of 0.1Hz to 48Hz. Further verification was conducted on the measurements acquired from the gadget. To validate the EEG signals, we performed an Alpha wave test and thereafter compared the obtained ECG data with a standard chest ECG. Utilizing EEG and ECG characteristics, a high level of 92.7% was achieved in the classification accuracy of mental stress [32].

In order to ascertain stress levels among the participants, S. Bhatnagar et.al introduced a music experimentation methodology. In this investigation, the author examined a sample of 45 participants aged between 13 and 21 years. The study utilized the EEGnet model architecture, a condensed convolutional neural network distinguished by a Relu activation function. An experiment was conducted using the mother wavelet decomposition technique on electroencephalogram signals ranging from 0 to 60 Hz frequency. The signals were divided into 5 frequency bands. The positions of mounting included frontal, temporal, partial, and central. Key characteristics of an experiment are the signals generated at the frontal and temporal positions among the frequency range of 8–16 Hz. The deep learning EEGnet architecture in the experimental investigation generated a precision of 99.45% for the alpha band [33].

Thi-Dung Tran et.al developed a dataset called SADVAW (Analysis of Stress in Korean Movies via Valence and Arousal Dimensions in Wild Settings) which captures video clips from several Korean movies displaying a diverse array of face expressions. The SADVAW dataset presents measurements of both valence and arousal in continuous dimensions. A comprehensive statistical analysis of the dataset is presented in this study. Additionally, they looked into the relationship between continuous dimensions and stress. Additionally, utilizing the SADVAW dataset, a deep learning-based model for stress detection was created [34].

Newly proposed by Nishtha Phutela et al., a stress classification method utilizes an EEG signal. Analysed were EEG signals acquired from thirty-five participants utilizing four EEG sensors that are part of a 4-electrode MUSE EEG monitor that is available for purchase. Stress elicitation material consisted of four selected movie excerpts. Two clips were chosen to elicit high levels of stress due to their inclusion of emotionally stimulating scenes. The last two short films were selected for their lack of stress-inducing elements, namely due to their abundance of humorous situations. Newly proposed by Nishtha Phutela et al., a stress classification method utilizes an EEG signal. EEG signals from 35 subjects were analyzed using four EEG sensors that were part of a commercially available 4-electrode MUSE EEG monitor [20].

Mhaouch, Ayoub et.al. focused through their work on achieving the automatic stress detection from EEG signals, to help clinicians to get the true diagnosis in an early stage. For this the author has implemented RNN model for automatic stress detection. The implemented RNN uses GRU along with the FFT transformation on EEG signals on the dataset which was available from Kaggle. The EEG classification results have reached 97.23% for train, 93.68% for validation and 88.86% for the test process, by implementing GRU based SGD optimizer networks. To further improve the results author implemented Adam optimizer achieving results equal to 99.53%, for the train, 94.98% for the validation and 89% for the test process. Moreover, stress emotions have been well detected as demonstrated by the confusion matrix results [35].

Sentiment Analysis (SA) is helpful in identifying the emotions and mental stress in the human brain. A.R. Kathole et.al. has carried out the experimentation on development of emotions and stress recognition system to detect the real time depression using deep learning on EEG Signals. After getting the dataset and pre-processing techniques the extraction of special features was carried out. Further with the aid of a Conditional Variational Autoencoder (CVA), the deep features were extracted from the pre-processed signals. The weights were optimized using the Adaptive Egret Swarm Optimization Algorithm (AESOA) so that the weighted fused features can be passed to Cascaded Deep Temporal Convolution Network with Attention Mechanism (CDTCN-AM) which was used to recognize stress and emotion[36].

Y. Badr et.al. performed the review of different articles on evaluating mental stress by deep learning using EEG signals. The review focuses on data representation, individual deep neural network model architectures, hybrid models, and results amongst others. The contributions of the paper address important issues such as data representation and model architectures. Out of all reviewed papers, 67% used CNN, 9% LSTM, and 24% hybrid models. Based on the reviewed literature, author analyzed that dataset size and different representations contributed to the performance of the proposed networks. Raw EEG data produced classification accuracy around 62% while using spectral and topographical representation produced up to 88%. The review encourages the exploration of innovative avenues, such as EEG data image representations concurrently with GCN, to mitigate the impact of inter-subject variability[37].

Sahithi, R. et.al. in another survey paper delves into the emerging realm of stress detection through EEG signals to employ Deep Learning algorithms. The paper assesses various approaches, including preprocessing methods, feature extraction, and various deep-learning models applied to EEG data. It sheds light on the obstacles and opportunities linked with stress detection using EEG signals, underscoring the importance of robust models in practical contexts[38].

Aishwarya B.N. et.al. focused on a comprehensive exploration of EEG-based emotion recognition, with a particular focus on leveraging RNN architectures, LSTM & GRU. EEG Brainwave dataset was used for experimentation. The dataset features signals obtained from frontal and temporal brain lobes, categorized into distinct emotional states encompassing positive, neutral, and negative emotions. The analysis spans four distinct scenarios, each representing different combinations of features and preprocessing strategies. The study also emphasis on the importance of meticulous feature selection and preprocessing in optimizing model accuracy and robustness, highlighting the intricate interplay between data representation, model architecture, and task-specific requirements[39].

Rajeswari Immanuel et.al. used a real time dataset which includes 15 subjects (7 Males and 8 Females) and their EEG signals are recorded using video stimuli. The real time data was preprocessed and features were extracted from the preprocessed data using different feature extraction methods. The accuracy and loss of model were calculated and compared with raw and preprocessed data. The proposed model - EEGEM (Electroencephalogram Ensemble Model) which is a combination of LSTM and CNN was compared with other machine and deep learning techniques. The accuracy achieved using this model is 95.56%[40].

S. Jerritta et.al. introduced Stress-Net, a new LSTM model for extracting temporal features while enhanced extreme learning machines were employed for better classification with less computational complexity. The different data sources were used to collect the EEG signals in which the collected signals are preprocessed for evaluating the proposed model. Additionally, the experiments were performed by DEAP and Kaggle datasets as well as performance parameters and compared by conventional Fused Support vector machines (F-SVM),BI-Long Short-Term Memory (BILSTM), Random Forest (RF) and Deep Convolutional Neural network (DCNN). Results shows that proposed Stress-Net model based on EEG signal has better performance than other conventional ones in stress detection and for diagnosing classify the stress-levels[41]. Following table 1 represents tabular literature review summary of most of the work done by the researchers in this field.

**Table 1: Literature Review Summary**

| Ref.No. | Insights | Methods Used | Limitations | Results |
|---|---|---|---|---|
| [35] | The paper presents a deep learning approach utilizing a GRU-based RNN model for automatic stress detection in EEG signals, achieving high accuracy and effective emotional valence classification. | Pre-processing with FFT transformation on EEG signals<br>Implementation of GRU model with Adam and SGD optimizers | Reduced number of parameters, complexity<br>No other limitations mentioned in the paper | EEG classification accuracy: Train 99.53%, Validation 94.98%<br>Stress emotions well detected with high accuracy. |
| [36] | The study employs a Cascaded Deep Temporal Convolution Network with Attention Mechanism for real-time mental stress and emotional valence detection using EEG signals and deep learning techniques. | EEG signal-based stress and emotion detection system.<br>Conditional Variational Autoencoder for deep feature extraction.<br>Adaptive Egret Swarm Optimization for weight optimization.<br>Cascaded Deep Temporal Convolution Network with Attention Mechanism. | | Developed a reliable Emotion and Stress Recognition system.<br>Showcased effectiveness against traditional models. |
| [37] | The review highlights the effectiveness of CNNs and LSTMs in detecting mental stress from EEG signals, achieving up to 88% accuracy with advanced data representations. | CNN, LSTM, and hybrid models utilized for mental stress evaluation.<br>Data representation and model architectures are key focus areas. | Generalizability across different deep learning models is unclear.<br>Individual differences in EEG responses need further investigation. | Raw EEG data accuracy: around 62%.<br>Spectral and topographical representation accuracy: up to 88%. |
| [38] | The paper discusses various deep learning models applied to EEG data for stress detection, emphasizing the importance of robust models for accurately identifying mental | Preprocessing methods, feature extraction, deep-learning models applied to EEG data<br>Assessing obstacles and opportunities in stress detection using EEG signals | Obstacles and opportunities in stress detection using EEG signals.<br>Importance of robust models in practical contexts. | |

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| | stress and emotional valence. | | | |
| [39] | The study employs LSTM and GRU architectures for detecting emotional states from EEG signals, emphasizing feature selection and preprocessing to enhance model accuracy in recognizing mental stress and emotional valence. | RNN architectures: LSTM and GRU<br>Feature selection and preprocessing techniques | Emphasis on feature selection and preprocessing for model optimization.<br>Interplay between data representation, model architecture, and task-specific requirements. | LSTM and GRU models evaluated for emotion recognition accuracy.<br>Importance of feature selection and preprocessing techniques highlighted for model optimization. |
| [40] | The paper presents EEGEM, an ensemble model combining LSTM and CNN, achieving 95.56% accuracy in detecting emotional states from EEG signals, enhancing mental stress and emotional valence detection. | EEG signal preprocessing and feature extraction methods used.<br>EEGEM combines LSTM and CNN for emotion detection. | | EEGEM model achieved 95.56% accuracy in emotion detection.<br>Outperformed other existing machine and deep learning models. |
| [41] | The proposed model utilizes LSTM for temporal feature extraction and enhanced extreme learning machines for efficient classification of mental stress and emotional valence from EEG signals. | LSTM for temporal features extraction<br>Enhanced extreme learning machines for classification with less complexity | Needs better performance and computational overhead improvements.<br>Requires evaluation across multiple datasets for robustness. | Proposed model outperforms conventional stress detection systems.<br>Achieves high accuracy in stress detection and classification. |
| [42] | The study enhances emotion recognition through a modified Convolutional Fuzzy Neural Network, achieving 98.21% accuracy for | Modified Convolutional Fuzzy Neural Network (CFNN)<br>Hybrid deep learning models and other techniques | Conventional machine learning algorithms caused inconsistent emotion recognition.<br>Complexity of EEG recordings and data analysis | Average accuracy: 98.21% for valence, 98.08% for arousal<br>Outperformed state-of-the-art methods in emotion recognition. |

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| | valence and 98.08% for arousal using EEG signals. | | led to inconsistent results. | |
| [43] | The proposed LSTM approach effectively detects mental stress in EEG signals, achieving approximately 94% accuracy, but does not specifically address emotional valence detection. | LSTM network for real-time stress detection.<br>Utilizes raw EEG signals without manual feature engineering. | | Achieved approximately 94% accuracy in stress detection.<br>Evaluated on DEAP dataset with 32 subjects. |
| [44] | The research presents a GAN model integrating deep learning with EEG to enhance emotion detection accuracy, focusing on mental stress and emotional valence through advanced neural network techniques. | GAN model with self-attention and residual neural networks<br>Autoencoder substitution for discriminator and reconstruction loss function | Overcoming vanishing gradient problem with self-attention mechanism and residual block.<br>No specific limitations mentioned in the abstract. | Model performs exceptionally well on emotion recognition test.<br>Emphasizes the role of interaction design frameworks in usability enhancement. |
| [45] | The study employs deep learning techniques to classify stress states using single-channel EEG and GSR data, achieving high predictive accuracy in a VR interview context. | Single-channel EEG and GSR data<br>Five CNN architectures and one Vision Transformer model | | Multiple-column structure achieved highest AUROC value of 0.954.<br>ResNet-152 excelled with GSR AUROC of 0.944. |
| [46] | The study employs a parallel TCN-SBU-LSTM architecture to analyze physiological signals for continuous emotional state detection, focusing on arousal and | Parallel TCN-SBU-LSTM architecture for emotion detection.<br>Grid search and 5-fold cross validation for hyperparameter tuning. | | Average root mean square error of 1.585 achieved.<br>Consistent performance across different emotional scenarios. |

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| | valence estimation in various scenarios. | | | |
| [47] | The paper proposes a CNN-TLSTM model for detecting mental stress levels using EEG and pulse rate, achieving an average accuracy of 97.86% in classification. | EEG signals and pulse rate recording.<br>CNN-TLSTM model with attention mechanism for classification. | | Average accuracy of CNN-TLSTM model is 97.86%.<br>Technique outperforms most existing state-of-the-art methods. |
| [29] | The study focuses on a hybrid deep learning model for stress detection using EEG signals, but it does not specifically address emotional valence detection. | Deep learning techniques: CNN, LSTM, BiLSTM, GRU, RNN<br>Hybrid combination of DWT-based CNN, BiLSTM, GRU | Complexity and significant parameter tuning required higher running time.<br>Tedious task in selecting different hybrid combinations for validating models. | The proposed hybrid model performed better in classification accuracy compared to other models.<br>Matrices, convergence, and ROC curves were used for visual comparison of the hybrid models. |
| [48] | The paper focuses on stress detection using wearable sensor data, specifically the Emphatical E4 wristband, rather than EEG for mental stress and emotional valence detection. | Long-Short Term-Memory (LSTM) network for stress detection.<br>Integrated Gradients for model explainability and feature highlighting. | Not Applicable | Not Applicable |
| [49] | The research presents a DWT-based hybrid deep learning model (CNN-BLSTM) for detecting mental stress from EEG signals, achieving a classification accuracy of 99.20%. | DWT-based hybrid deep learning model using CNN-BLSTM<br>Automated feature selection technique using CNN | EEG signals require interpretation by trained physicians due to complexity.<br>Prior work like CNN-based LSTM models have lower accuracy. | The suggested model achieved a classification accuracy of 99.20%.<br>The model was validated with a classification result of 98.10% using the stratification tenfold cross-validation method. |
| [50] | The study employs one-dimensional convolutional neural networks combined with | One-dimensional convolutional neural network (CONVID) | Not Applicable | The CONVlD+BiLSTM model achieved the highest emotion |

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| | bidirectional LSTM to achieve an 88.03% accuracy in detecting mental stress and emotional valence from EEG data. | Bidirectional long-short term memory network (BiLSTM)<br>Bidirectional gated recurrent unit (BiGRU) networks | | detection accuracy of 88.03%.<br>The DL models outperformed conventional shallow learning approaches. |
| [51] | The paper focuses on using SVM algorithms for detecting mental stress through EEG signals, rather than a deep learning approach for emotional valence detection. | EEG signals for detecting mental stress levels.<br>SVM algorithm for improving accuracy in stress detection. | Not Applicable | SVM-based system accurately detects mental stress levels.<br>Overall classification accuracy demonstrated in study results. |
| [52] | The study presents a CNN model that classifies stress levels from EEG signals, achieving 98.95% accuracy, demonstrating the effectiveness of deep learning in mental stress detection. | Convolutional Neural Network (CNN) model<br>Machine Learning and Deep Learning techniques | Not Applicable | Achieved 98.95% accuracy in stress level predictions.<br>Demonstrated potential of Deep Learning for health monitoring. |
| [48] | The paper focuses on stress detection using wearable sensor data, specifically through an LSTM network, rather than EEG for mental stress and emotional valence detection. | Long-Short Term-Memory (LSTM) network<br>Deep Generative Ensemble of conditional GANs (LSTM DGE) | Not Applicable | LSTM DGE outperforms state-of-the-art by 3% recall, 7.18% precision.<br>Integrated Gradients show overlap with existing stress detection features. |
| [53] | The study employs a deep Q neural network for classifying EEG features, effectively detecting mental stress and emotional valence with high accuracy and performance metrics. | Fuzzy-based deep learning techniques<br>Fuzzy neural network (FNN) and deep Q neural network | Limited availability of labeled EEG data for training classifiers<br>Challenges in training effective classifiers with constrained labeled samples | Accuracy: 96%<br>Precision: 90% |

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| [54] | The paper proposes a deep learning framework utilizing EEG signals for emotion detection, achieving high accuracy in recognizing emotional valence, arousal, and dominance dimensions through a recurrent neural network. | Recurrent neural network algorithm as a classifier<br>Feature extraction algorithm based on event-related desynchronization and event-related synchronization analysis | Not Applicable | 92.13% accuracy for valence dimension<br>92.67% accuracy for arousal dimension |
| [55] | The study focuses on estimating mental stress levels using EEG data integrated with a Serious Game, employing a recurrent neural network for classification, achieving up to 94% accuracy. | Electroencephalographic (EEG) system integration with Serious Game.<br>Deep learning using recurrent neural network (RNN) with GRU. | Not Applicable | RNN model predicts stress levels with up to 94% accuracy.<br>Deep Learning enhances stress prediction using EEG and Serious Games. |
| [56] | The paper does not specifically discuss a deep learning approach for mental stress and emotional valence detection using EEG. It focuses on feature selection and sampling methods instead. | Sequential backward selection (SBS) for feature selection.<br>Adaptive synthetic (ADASYN) sampling for imbalanced data. | Not Applicable | Delta and theta features comprise 50% of selected features.<br>Maximum balanced accuracy of 94.8% in stress detection. |

## III. CONCLUSION

The increasing prevalence of stress in modern society necessitates robust and scalable detection methods. EEG-based stress detection, powered by machine learning and deep learning, represents a promising avenue for addressing this need. By leveraging the temporal precision and affordability of EEG, researchers have developed models capable of achieving remarkable classification accuracies. However, significant challenges remain, including computational complexity, dataset diversity, and real-time applicability.

This review highlights the potential of hybrid ML-DL frameworks, advanced feature extraction techniques, and lightweight algorithms for improving stress detection systems. Future research should focus on optimizing model architectures, validating systems on real-time datasets, and addressing inter-individual variability in EEG signals. By overcoming these barriers, the field can move closer to deploying practical stress detection solutions, ultimately enhancing mental health management and preventive care.

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