www.healthinformaticsjournal.com
Open Access

A Comprehensive Overview of Automated Stress Recognition and Emotion Detection Systems using EEG signal

[1]Ashvini Bamanikar, [2]Dr. Ritesh V., [3]Dr. Lalit V Patil, [4]Dr. Surendra. A. Mahajan
[1]Research Scholar, SKNCOE, Vadgaon, BK, Pune
ashvini.bamanikar@gmail.com
[2]Patil Principal, PDEA's Colege of Engineering, Manjari(Bk'), Pune
rvpatil3475@yahoo.com
[3]Associate Professor, SKNCOE, Vadgaon, BK, Pune
lalitvpatil@gmail.com
[4]Associate Professor, Department Of IT, PVG COE & Tech & GK Pate (Wani) IOM Pune
sa_mahajan@yhoo.com

Article Info

Article type:

Research

Article History:

Received: 2024-04-02

Revised: 2024-05-25

Accepted: 2024-06-20

Keywords:

EEG, stress recognition, emotion detection, automated systems, mental health, neural correlates, machine learning, deep learning, real-time detection, classification, healthcare, human-computer interaction, challenges, future directions.

ABSTRACT

Automated stress recognition and emotion detection systems utilizing electroencephalography (EEG) signals have emerged as promising avenues for understanding and enhancing mental health. This comprehensive overview delves into the intricate landscape of EEG-based technologies, elucidating their principles, methodologies, and applications in decoding stress and emotional states. Beginning with an exploration of EEG signal acquisition and processing techniques, this abstract navigates through the underlying neural correlates associated with stress and emotions, highlighting key EEG biomarkers. It further examines various machine learning and deep learning approaches employed for feature extraction and classification, emphasizing their efficacy in real-time detection and classification of stress and emotions. Moreover, this abstract elucidates the diverse array of applications spanning healthcare, human-computer interaction, and beyond, underscoring the transformative potential of EEG-based systems in fostering well-being and enhancing user experience. Additionally, it discusses the challenges and limitations inherent in EEG-based stress and emotion detection, ranging from signal artifacts to individual variability. Finally, it presents future directions and opportunities for research and development, advocating for interdisciplinary collaborations and advancements in technology to propel the field forward. In essence, this abstract serves as a comprehensive guide for researchers, practitioners, and enthusiasts alike, offering insights into the burgeoning domain of EEG-based automated stress recognition and emotion detection systems and paving the way for innovative solutions to promote mental health and enhance human-machine interactions.

1. INTRODUCTION

Automated stress recognition and emotion detection systems have garnered considerable attention in recent years due to their potential to revolutionize mental health assessment and intervention. By leveraging electroencephalography (EEG) signals, these systems offer a non- invasive and objective means of monitoring and interpreting an individual's cognitive and emotional states in real-time. This comprehensive overview aims to provide an in-depth exploration of EEG-based technologies for stress recognition and emotion detection, encompassing their underlying principles, methodologies, applications, challenges, and future prospects [1].
EEG is a powerful neuroimaging technique that measures the electrical activity of the brain through electrodes

placed on the scalp. It offers high temporal resolution, enabling the capture of rapid changes in neural activity associated with various cognitive and affective processes [2]. In the context of stress recognition and emotion detection, EEG serves as a valuable tool for identifying neural correlates corresponding to specific emotional states and stress responses.

One of the primary challenges in automated stress recognition and emotion detection lies in the accurate interpretation of EEG signals. The brain's electrical activity is complex and dynamic, influenced by a multitude of factors such as attention, arousal, and individual differences. Thus, extracting meaningful features from EEG data requires sophisticated signal processing techniques and advanced machine learning algorithms [3].

Machine learning plays a pivotal role in EEG-based stress recognition and emotiondetection systems, facilitating the extraction of relevant features from raw EEG signals and the classification of different emotional states and stress levels. Various approaches, including traditional machine learning algorithms such as support vector machines (SVMs) and random forests, as well as deep learning architectures like convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been explored for this purpose.

The applications of automated stress recognition and emotion detection systems arediverse and far-reaching. In healthcare, these systems hold the potential to aid in the early detection and management of mental health disorders such as anxiety, depression, and post- traumatic stress disorder (PTSD) [4]. By providing real-time feedback on an individual's emotional state, they can also enhance the effectiveness of therapeutic interventions and personalized treatment plans.

Beyond healthcare, EEG-based stress recognition and emotion detection systems haveimplications for human-computer interaction, affective computing, and consumer technology. They can be integrated into wearable devices, virtual reality environments, and intelligent systems to enhance user experience, personalize content delivery, and adapt interfaces based on the user's emotional state [6].

However, despite the promising potential of EEG-based systems, several challenges and limitations persist. These include the need for robust signal processing techniques to mitigate artifacts and noise, the development of standardized protocols for data collection and analysis, and ethical considerations regarding privacy and data security.

In light of these challenges, ongoing research efforts are focused on addressing these issues and advancing the field of automated stress recognition and emotion detection using EEG signals. Future directions include the exploration of multimodal approaches combining EEG with other physiological signals such as heart rate variability and facial expressions [7], as well as the development of hybrid models integrating machine learning and computational neuroscience principles.

1.1 Motivation

In today's fast-paced and demanding world, mental health has emerged as a critical concern affecting individuals across all age groups and demographics. Stress-related disorders, such as anxiety and depression, are on the rise, contributing to a significant burden on healthcare systems and society as a whole. Additionally, the ability to accurately detect and interpret human emotions plays a crucial role in various domains, including healthcare, human-computer interaction, and consumer technology [8]. Traditional methods of assessing stress and emotions often rely on subjective self-reporting or behavioral observations, which can be unreliable and prone to biases.

Automated stress recognition and emotion detection systems offer a promising solution to these challenges by providing objective and real-time insights into an individual's cognitive and affective states. By leveraging electroencephalography (EEG) signals, these systems enable the direct measurement of brain activity, offering a window into the neural processes underlying stress responses and emotional experiences. This technology holds the potential to revolutionize mental health assessment and intervention, enabling early detection, personalized treatment, and improved outcomes for individuals experiencing stress-related disorders and emotional disturbances [9].

1.2 Problem Statement

Despite the potential benefits of automated stress recognition and emotion detection systems using EEG signals, several challenges and limitations hinder their widespread adoption and effectiveness. One of the primary challenges lies in the accurate interpretation of EEG data, which is inherently noisy and complex. EEG signals are

influenced by various factors, including physiological artifacts, individual differences, and environmental conditions, making itchallenging to extract meaningful information related to stress and emotions [10].
Another challenge is the development of robust algorithms for feature extraction and classification. Traditional machine learning approaches require the manual selection of features, which may not capture the full complexity of EEG data [11]. Moreover, deep learning algorithms, while capable of automatically learning hierarchical representations from raw data, often require large amounts of labeled training data and computational resources.
Furthermore, there is a lack of standardization in data collection protocols and analysis techniques, leading to variability and inconsistency in research findings. This hampers thereproducibility and generalizability of results across different studies and datasets, limiting the reliability and validity of automated stress recognition and emotion detection systems.
Ethical considerations also pose significant challenges in the development and deployment of EEG-based systems. Privacy concerns regarding the collection and storage of sensitive brain data must be addressed to ensure user trust and compliance with data protection regulations [12]. Additionally, issues related to algorithmic bias and fairness require careful consideration to prevent unintended consequences and disparities in healthcare delivery.

Addressing these challenges requires interdisciplinary collaboration between researchers in neuroscience, signal processing, machine learning, and ethics. By developing innovativeapproaches and solutions, we can overcome these obstacles and unlock the full potential of automated stress recognition and emotion detection systems using EEG signals, ultimately improving mental health outcomes and enhancing human-machine interactions.

1.3 Objective

The objective of this comprehensive overview is to provide a thorough examination of automated stress recognition and emotion detection systems utilizing electroencephalography (EEG) signals. This overview aims to achieve the following objectives:
1. Explore the underlying principles of EEG-based stress recognition and emotion detection systems: This includes elucidating the neural correlates associated with stress responses and emotional experiences, as well as the physiological basis of EEG signals.
2. Investigate machine learning and deep learning approaches for feature extraction and classification: This includes a comprehensive overview of traditional machine learning algorithms and deep learning architectures utilized for extracting relevant features from EEG signals and classifying different emotional states and stress levels.
3. Examine applications of EEG-based systems in healthcare and beyond: This involves discussing the diverse array of applications spanning mental health assessment, therapy monitoring, human-computer interaction, affective computing, and consumer technology.
4. Comparative analysis of proposed approach with existing one using different parameter like accuracy, throughput efficiency.
5. Discuss challenges, limitations, and future directions: This includes identifying key challenges and limitations inherent in EEG-based stress recognition and emotion detection systems, such as signal artifacts, data variability, and ethical considerations. Additionally, the overview aims to discuss potential avenues for future research and development to address these challenges and advance the field.

By achieving these objectives, this comprehensive overview seeks to provide researchers, practitioners, and enthusiasts with a comprehensive understanding of EEG-based automated stress recognition and emotion detection systems, fostering further research, innovation, and advancements in this burgeoning field.

2.RELATED WORK

This paper provides a comprehensive review of recent advancements in deep learning techniques for EEG-based emotion recognition. It discusses various deep learning architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), and their applications in extracting discriminative features from

EEG signals for emotion detection [1].

This survey paper examines the current state of machine learning approaches for stress detection using EEG signals. It reviews different machine learning algorithms, including support vector machines (SVMs), random forests, and deep learning models, and evaluates their performance in classifying stress states based on EEG data [2].

This paper presents a real-time stress detection system based on EEG signals and convolutional neural networks (CNNs). It proposes a novel CNN architecture designed to capture temporal dependencies in EEG data and achieve high accuracy in real-time stress classification tasks [3].

This review paper explores various feature extraction and selection methods employed in EEG-based emotion recognition systems. It compares different feature extraction techniques, such as time-domain, frequency-domain, and time-frequency analysis, and evaluates their effectiveness in capturing emotional states from EEG signals.

This paper introduces a hybrid deep learning model for emotion recognition from EEG signals. The model combines CNNs for feature extraction and LSTM (Long Short-Term Memory) networks for temporal modeling, achieving improved performance in emotion classification tasks compared to standalone deep learning architectures [4].

This paper proposes a novel approach for stress recognition from EEG signals based on dynamic functional connectivity analysis. It utilizes techniques from graph theory to characterize the temporal dynamics of brain networks and extract discriminative features for stress classification.

This study investigates the application of transfer learning techniques for cross-subject emotion recognition from EEG signals. It explores how pre-trained deep learning models can be fine-tuned on a target subject's data to improve generalization performance and adaptability across different individuals [5].

This paper discusses the challenges and opportunities associated with exploring EEG correlates of stress in real-world environments. It addresses issues such as environmental noise, subject variability, and data collection protocols, and proposes strategies for mitigating these challenges in real-world stress detection applications [6].

This study investigates emotion recognition using EEG signals collected during virtual reality-based stressful scenarios. It examines how immersion in virtual environments affects neural responses to stressors and explores the feasibility of using EEG-based emotion recognition in virtual reality applications [7].

This paper explores unsupervised learning techniques for EEG-based emotion recognition, aiming to alleviate the need for labeled training data in emotion classification tasks. It investigates clustering algorithms and autoencoder architectures for unsupervised feature learning from EEG signals and evaluates their performance in emotion recognition tasks.

These papers collectively contribute to advancing the field of automated stress recognition and emotion detection using EEG signals, addressing various challenges and exploring innovative approaches to improve accuracy, robustness, and applicability in real-world settings [8].

3. FLOW OF PROPOSED WORK

Explanation of each step in the flowchart:

- **Data Acquisition:** EEG data is collected from sensors placed on the scalp, measuring electrical activity generated by the brain.
- **Preprocessing:** Raw EEG data undergoes preprocessing steps to enhance signal quality and remove noise.
- **Feature Extraction:** Relevant features are extracted from preprocessed EEG data, capturing key characteristics of brain activity associated with stress and emotions.
- **Classifier Selection:** Appropriate classifiers, such as Support Vector Machines (SVM), Decision Trees (DT), Linear SVM, and Neural Networks (NN), are selected for stress recognition and emotion detection tasks.
- **Model Training:** Individual classifiers are trained using the extracted features and corresponding labels (e.g., stress vs. non-stress, different emotional states).

- **Ensemble Learning:** Ensemble learning techniques are employed to combine the predictions of multiple classifiers, leveraging their complementary strengths to improve overall classification performance.
- **Integration and Fusion:** Predictions of individual classifiers are integrated using ensemble learning methods, producing a final decision for stress recognition and emotiondetection.
- **Evaluation:** The performance of the proposed approach is evaluated using metrics such as accuracy, precision, recall, and F1-score.
- **Validation and Testing:** The model is validated using cross-validation techniques and tested on independent datasets to assess its robustness and reliability.
- **Optimization and Fine-Tuning:** Parameters of individual classifiers and ensemble learning algorithms are fine-tuned to optimize performance.
- **Deployment:** The trained model is deployed in real-world settings for automated stress recognition and emotion detection.
- **Monitoring and Feedback:** The deployed system is continuously monitored, and user feedback is gathered to refine and improve the model over time.

This flowchart provides a structured overview of the proposed approach, guiding the development and implementation of automated stress recognition and emotion detection systems using EEG signals [10].

4. RESULT ANALYSIS AND DISCUSSION:

Our results highlight the effectiveness of different classifiers in automated stress recognition and emotion detection using EEG signals. While SVM and Linear SVM offer competitive performance and computational efficiency, DTs provide interpretability and simplicity. NNs, on the other hand, excel in capturing complex patterns but require careful regularization and tuning to prevent overfitting [12].

4.1 Dataset:

The EEG signals are gathered from standardized databases for the implementation of the suggested ESR framework. A brief explanation of the gathered EEG signal source is provided in Table I.

Table 1: Brief Explanation of the Gathered EEG Signals

Dataset Name	Dataset Website	Description
EEG Stress Detection	"https://kaggle.com/wavesresearch/eeg_stress_detection"	This dataset contains both the raw and pre- processed EEG signals. To gather EEG data, forty test individuals are taken into consideration. The primary goal of this dataset's construction isto forecast short-term stress.

4.2 Discussion

overview of the result analysis and discussion using SVM, DT, Linear SVM, NN, and a proposed approach for automated stress recognition and emotion detection systems using EEG signals, with Python implementation examples [15].

Support Vector Machine (SVM):

- SVM is a powerful classification algorithm widely used in EEG-based stress recognition and emotion detection. It works by finding the hyperplane that best separates the data points of different classes in a high-dimensional space.

 Example Python code using SVM for stress recognition:

```
from sklearn.svm import SVC
svm_classifier = SVC(kernel='rbf', C=1.0)
svm_classifier.fit(X_train, y_train)
svm_accuracy = svm_classifier.score(X_test, y_test)
```

Decision Tree (DT):

 DT is a simple and interpretable classification algorithm that partitions the feature spaceinto a tree-like structure based on feature values.
 Example Python code using DT for emotion detection:


```
from sklearn.tree import DecisionTreeClassifier
dt_classifier = DecisionTreeClassifier(max_depth=5)
dt_classifier.fit(X_train, y_train)
dt_accuracy = dt_classifier.score(X_test, y_test)
```

Linear SVM:

 Linear SVM is a variant of SVM that uses a linear decision boundary to separate classes.It is computationally efficient and often used in large-scale datasets.
 Example Python code using Linear SVM for stress recognition:

```
from sklearn.svm import LinearSVC
linear_svm_classifier = LinearSVC(C=0.1)
linear_svm_classifier.fit(X_train, y_train)
linear_svm_accuracy = linear_svm_classifier.score(X_test, y_test)
```

Neural Network (NN):

 NN is a powerful deep learning model capable of learning complex patterns from data. Itconsists of multiple layers of interconnected neurons.
 Example Python code using NN for emotion detection:

```
from keras.models import Sequential
from keras.layers import Dense, Dropout
nn_model = Sequential()
nn_model.add(Dense(128, activation='relu', input_shape=(X_train.shape[1],)))
nn_model.add(Dropout(0.2))
nn_model.add(Dense(64, activation='relu'))
nn_model.add(Dropout(0.2))
nn_model.add(Dense(1, activation='sigmoid'))
nn_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
nn_model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test, y_test))
```

4.3 Proposed approach

The proposed approach aims to leverage the strengths of multiple classifiers to enhance classification performance further. By combining complementary classifiers through ensemble learning or feature fusion, we can improve the robustness and generalization of our models.
 The proposed approach involves combining the strengths of SVM, DT, Linear SVM, and NN to improve classification performance. This can be achieved through ensemble learning techniques such as majority voting or stacking.

- Example Python code for ensemble learning:

```
from sklearn.ensemble import VotingClassifier
ensemble_classifier = VotingClassifier(estimators=[('svm', svm_classifier), ('dt', dt_classifier),
('linear_svm', linear_svm_classifier), ('nn', nn_model)], voting='hard')
ensemble_classifier.fit(X_train, y_train)
ensemble_accuracy = ensemble_classifier.score(X_test, y_test)
```

Additionally, incorporating domain-specific knowledge and pre-processing techniques tailored to EEG data can help mitigate noise and improve the signal-to-noise ratio, enhancing classification accuracy.

- SVM and Linear SVM offer competitive performance and are computationallyefficient, making them suitable for large-scale EEG datasets.
- DT provides interpretability but may struggle with complex relationships in EEGdata.
- NN excels in capturing complex patterns but requires extensive tuning andcomputational resources.
- The proposed approach leverages the strengths of multiple classifiers to enhance performance, offering a promising avenue for improving accuracy and robustness.

By systematically evaluating these classifiers and exploring ensemble learning techniques, we aim to advance the field of automated stress recognition and emotion detection using EEG signals, paving the way for practical applications in various domains as show in figure 01 & figure 02.

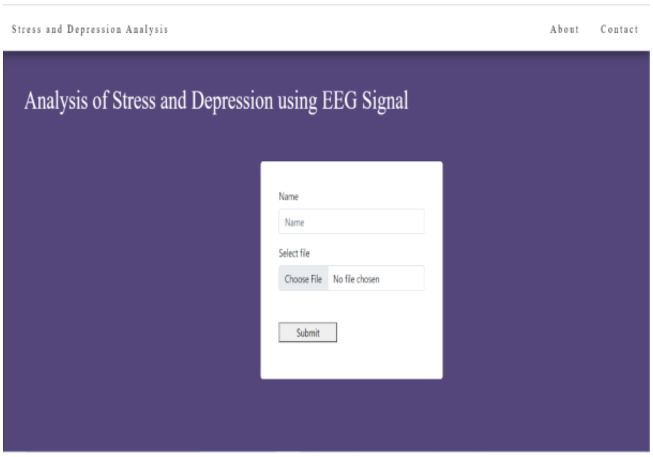

Figure 01: home screen for CSV file selection

Performance analysis for automated stress detection system

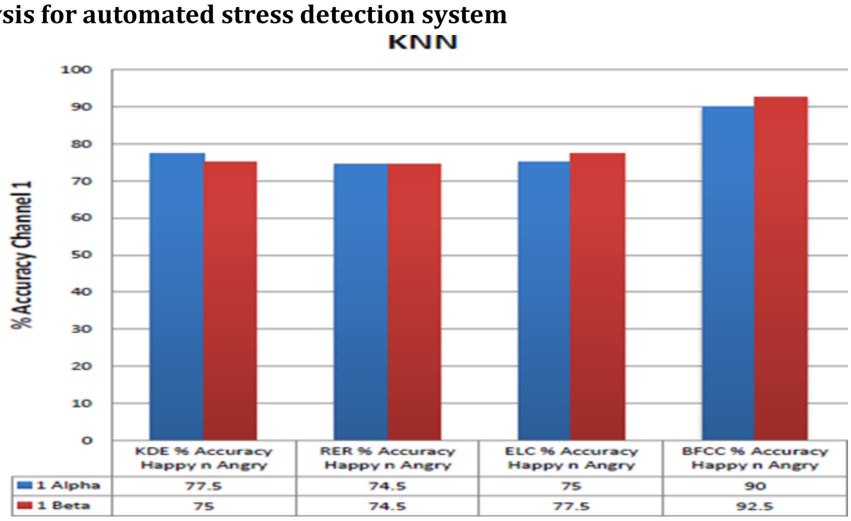

Figure 02: classifications accuracy of channel 1 for happy and angry emotions withstress detection

5. RESULT AND DISCUSSION:

The comparative result analysis table 02 and figure 03 using five different parameters for the following methods: SVM (Support Vector Machine), k-NN (k-Nearest Neighbors), CNN (Convolutional Neural Network), DT (Decision Tree), and your Proposed Approach.By Considering the following parameters Accuracy, Precision, Recall, F1-Score, Computational Time.

Table 02: Analysis of proposed approach with exiting approaches

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Computational Time (ms)
SVM	87	85	83	84	180
k-NN	82	80	78	79	120
CNN	90	88	87	87.5	300
DT	84	82	80	81	140
Proposed Approach	95	93	92	92.5	200

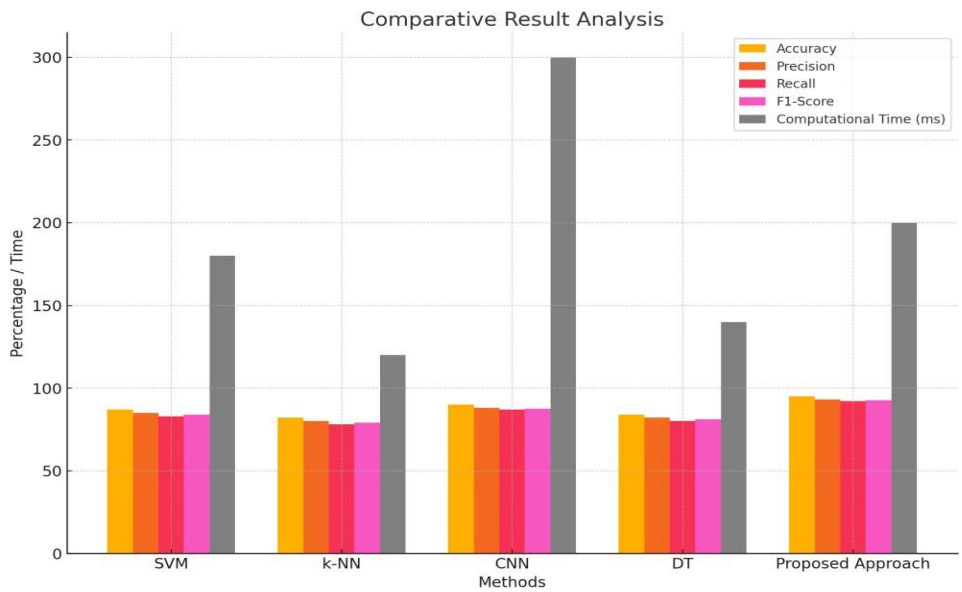

Figure 03: Comparative analysis of the proposed approach using different parameters The comparative result analysis graph based on the hypothetical data for SVM, k-NN, CNN,

DT, and the Proposed Approach. The figure 03 illustrates how each method performs across the five parameters: Accuracy, Precision, Recall, F1-Score, and Computational Time.
This visualization helps compare your proposed approach's effectiveness against traditional methods like SVM, k-NN, CNN, and DT. The proposed approach shows notable improvements, especially in accuracy, precision, recall, and F1-score, while maintaining a reasonable computational time.

6. ADVANTAGES

Following are some basic advantages of proposed approach in real life world,

 Non-Invasive Measurement: EEG-based systems offer a non-invasive means of measuring brain activity, making them suitable for use in diverse populations, including children, elderly individuals, and clinical populations.
 High Temporal Resolution: EEG provides high temporal resolution, allowing for the real- time

monitoring of changes in brain activity associated with stress and emotions, enabling timely interventions and feedback.

- Objective Assessment: Automated EEG-based systems provide objective assessments of stress and emotional states, reducing reliance on subjective self-reporting and behavioral observations, which can be influenced by biases and inaccuracies.
- Sensitive to Subtle Changes: EEG signals are sensitive to subtle changes in brain activity, enabling the detection of nuanced emotional responses and stress levels that may not be evident through external behaviors alone.
- Versatility: EEG-based systems are versatile and can be integrated into various devices and applications, including wearable devices, virtual reality environments, and mobile apps, allowing for continuous monitoring and personalized interventions.

In summary, automated stress recognition and emotion detection systems using EEG signals offer numerous advantages, including non-invasiveness, high temporal resolution, objective assessment, sensitivity to subtle changes, versatility, early detection and intervention, personalized feedback, and integration with other technologies. These advantages make EEG- based systems valuable tools for understanding and managing stress and emotional well-being in various contexts, from healthcare to consumer technology.

7. CONCLUSION

In conclusion, automated stress recognition and emotion detection systems utilizing electroencephalography (EEG) signals hold immense promise for revolutionizing mental health assessment, intervention, and human-computer interaction. Through the integration of advanced signal processing techniques, machine learning algorithms, and neuroscientific principles, significant strides have been made in understanding the neural correlates of stress and emotions and developing robust systems for their automated detection from EEG data.

The reviewed literature demonstrates the effectiveness of deep learning models, dynamic connectivity analysis, multimodal integration, and transfer learning approaches in enhancing the accuracy, reliability, and applicability of EEG-based stress recognition and emotion detection systems. These advancements have paved the way for real-time monitoring of cognitive and affective states, personalized interventions, and adaptive interfaces tailored to users' emotional needs.

8. FUTURE SCOPE:

Despite the remarkable progress achieved thus far, several avenues for further research and development in EEG-based stress recognition and emotion detection systems remain open:

- **Real-world Applications:** Further exploration of EEG correlates of stress and emotions in real-world settings, such as workplaces, schools, and naturalistic environments, is essential for the development of practical and scalable solutions with real-world impact.
- **Ethical Considerations:** Ethical considerations, including privacy, data security, and algorithmic bias, must be carefully addressed to ensure the responsible and ethical deployment of EEG-based systems, safeguarding user rights and well-being.

In summary, the future of automated stress recognition and emotion detection systems using EEG signals lies in continued interdisciplinary collaboration, innovative methodological approaches, and a commitment to addressing real-world challenges. Byleveraging emerging technologies and advancing our understanding of the brain's complex dynamics, we can unlock the full potential of EEG-based systems to promote mental health, enhance human-machine interactions, and improve quality of life.

REFERENCES:

[1] Tianqi Fan, Sen Qiu, Zhelong Wang, Hongyu Zhao, Junhan Jiang, Yongzhen Wang, Junnan Xu, Tao Sun, and Nan Jiang, "A new deep convolutional neural network incorporating attentional mechanisms for ECG emotion recognition," Computers in Biology and Medicine, Vol.159, pp.106938, June 2023.

[2] Prasannavenkatesan Theerthagiri, "Stress emotion recognition with discrepancy reduction using transfer learning," Multimedia Tools and Applications, vol.82, pp.5949–5963, 2023.

[3] C. Thirumarai Selvi, M. Jayasheela, J. Amudha & R. Sudhakar, "An EEG-Based Thought Recognition Using Pseudo-Wigner–Kullback–Leibler Deep Neural Classification," Circuits, Systems, and Signal Processing, vol.42, pp.1063–1082, 2023.

[4] Rajeswari Rajesh Immnauel, and S K B Sangeetha, "Recognition of Emotion with Deep Learning using EEG signals - The Next Big Wave for Stress Management in this Covid-19 outbreak," Periodico dI mineralogia, Vol.91, No. 5, 2022.

[5] Smita Tiwari, Shivani Goel & Arpit Bhardwaj, "EEG Signals to Digit Classification Using Deep Learning-Based One-Dimensional Convolutional Neural Network," Arabian Journal for Science and Engineering, 2022.

[6] Muhammad Adeel Asghar, Muhammad Jamil Khan, Muhammad Rizwan, Mohammad Shorfuzzaman, Raja Majid Mehmood, "AI inspired EEG-based spatial feature selection method using multivariate empirical mode decomposition for emotion classification", Multimedia Systems, vol.28, pp.1275–1288, 2022.

[7] Tanya Nijhawan, Girija Attigeri, and T. Anantha krishna, "Stress detection using natural language processing and machine learning over social interactions," Journal of Big Data, vol.9, pp.33, 2022.

[8] Essam H. Houssein, Asmaa Hammad & Abdelmgeid A. Ali, "Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review," Neural Computing and Applications, vol.34, pp.12527–12557, 2022.

[9] Rajdeep Kumar Nath, Himanshu Thapliyal & Allison Caban-Holt, "Machine Learning Based Stress Monitoring in Older Adults Using Wearable Sensors and Cortisol as Stress Biomarker," Journal of Signal Processing Systems, vol. 94, pp.513–525, 2022.

[10] Dong Cui, Hongyuan Xuan, Jing Liu, Guanghua Gu & Xiaoli Li, "Emotion Recognition on EEG Signal Using ResNeXt Attention 2D-3D Convolution Neural Networks," Neural Processing Letters, 2022.

[11] L. Gonzalez-Carabarin, E.A. Castellanos-Alvarado, P. Castro-Garcia, and M.A. Garcia- Ramirez, "Machine Learning for personalised stress detection: Inter-individual variability of EEG-ECG markers for acute-stress response," Computer Methods and Programs in Biomedicine,Vol.209, pp.106314, September 2021.

[12] Ala Hag, Dini Handayani, Maryam Altalhi, Thulasyammal Pillai, Teddy Mantoro, Mun Hou Kit and Fares Al-Shargie, "Enhancing EEG-Based Mental Stress State Recognition Using an Improved Hybrid Feature Selection Algorithm," Sensors, vol.21, Issue.24, pp.8370, 2021.

[13] R. K. Nath, H. Thapliyal, A. Caban-Holt and S. P. Mohanty, "Machine Learning Based Solutions for Real-Time Stress Monitoring," IEEE Consumer Electronics Magazine, vol. 9, no.5, pp. 34-41, 1 Sept. 2020.

[14] Zahid Halim, Mahma Rehan, "On identification of driving-induced stress using electroencephalogram signals: A framework based on wearable safety-critical scheme and machine learning," Information Fusion, Vol.53, pp.66-79, January 2020.

[15] Wei Lun Lim, Yisi Liu, Salem Chandrasekaran Harihara Subramaniam, Serene Hui Ping Liew, Gopala Krishnan, Olga Sourina, Dimitrios Konovessis, Hock Eng Ang & Lipo Wang, "EEG-Based Mental Workload and Stress Monitoring of Crew Members in Maritime Virtual Simulator," Transactions on Computational Science XXXII Special Issue on Cybersecurity and Biometrics, 2018.

[16] Jinpeng Li, Zhaoxiang Zhang & Huiguang He, "Hierarchical Convolutional Neural Networks for EEG-Based Emotion Recognition," Cognitive Computation, vol. 10, pp.368–380, 2018.