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Developing a Framework for Human Emotion Detection and Stress Analysis using Biomedical Signals

Abstract: In recent years, advances in machine learning techniques have opened up new options for automated recognition of emotional and stress states using electroencephalogram (EEG) signals. This work describes a thorough machine-learning approach to emotion and stress detection, which uses EEG data to create an accurate and dependable recognition system. The suggested methodology is a multi-step procedure that begins with the capture and preprocessing of EEG data, followed by feature extraction using wavelet transform and statistical methods. These features are then fed into a variety of machine learning classifiers, such as Support Vector Machines (SVM), Neural Networks (NN), and Decision Trees (DT), which discover patterns associated with distinct emotional and stress states.

Filtering to reduce noise and artefacts is part of the preprocessing phase, which ensures that the data used for the subsequent analysis is clean and meaningful. Feature extraction aims to capture both time-domain and frequency-domain properties of EEG data, which are essential for discriminating various mental states. The classifiers are trained and verified on a labelled dataset, allowing the system to learn and generalise patterns associated with different emotions and stress levels.

Our experimental results show that the proposed technique is highly accurate in recognizing emotional and stress states. The SVM classifier performs very well, with an accuracy of 92%, followed by Neural Networks at 89% and Decision Trees at 85%. These classifiers' performance is measured using metrics including accuracy, precision, recall, and the area under the Receiver Operating Characteristic (ROC) curve (AUC).

To demonstrate the success of our approach, we compared the ROC curves for filtered and unfiltered EEG data. The ROC curve for filtered data has a steeper rise and a higher AUC, indicating greater discriminative power and fewer false positives than unprocessed data. This emphasizes the relevance of preprocessing in improving the performance of classification models.

This study highlights the potential of applying machine learning approaches to automate emotion and stress assessment using EEG signals. The findings show that our suggested approach is a reliable tool for real-time mental health monitoring, with important implications for applications in healthcare, workplace stress management, and human-computer interaction. Future research will concentrate on integrating real-time EEG recording devices and investigating deep learning models to enhance detection accuracy and robustness.

Keyword: Emotion Recognition, Stress Detection, EEG Signals, Machine Learning, Support Vector Machines (SVM), Feature Extraction.

1. Introduction:

The detection and analysis of human emotions and stress levels has attracted a great deal of attention in the fields of neuroscience, psychology, and artificial intelligence. Emotions and stress have a significant impact on

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human behavior, cognition, and overall well-being, therefore accurate evaluation is vital in a wide range of applications [1], from mental health monitoring to improving human-computer interaction. Electroencephalogram (EEG) signals, which capture electrical activity in the brain, offer a non-invasive, real-time method of evaluating these mental processes. Unlike previous methods that rely on self-reported measures or physiological markers such as heart rate and skin conductance, EEG signals provide direct insights into cerebral processes, allowing for a more nuanced understanding of emotional and stress responses.

Machine learning has revolutionized the processing and interpretation of EEG signals, allowing sophisticated models to recognize complex patterns associated with diverse mental states [2]. Machine learning techniques such as Support Vector Machines (SVM), Neural Networks (NN), and Decision Trees (DT) have shown promise in identifying significant features from EEG data and categorizing them into discrete emotional and stress categories. These models use vast amounts of data to explain and generalize the complicated relationships between EEG signal characteristics and psychological states, thus boosting the accuracy and reliability of emotion and stress detection systems [3].

1.1 Motivation:

The motivation for this study is twofold. First, there is an urgent need for better mental health care technologies that can detect emotional and stress states early on and monitor them continuously. Such technology can help with timely therapies, lowering the risk of serious mental health concerns, and increasing patient outcomes. Second, boosting human-computer connection by tailoring systems to users' emotional and stress levels can have a major impact on both user experience and productivity [4]. Adaptive learning systems that adapt to students' stress levels, for example, can contribute to a more conducive learning environment, whilst stress-aware workplace apps can assist managers in better managing staff well-being.

Given these incentives, this study provides a comprehensive machine learning technique to automated emotion and stress recognition via EEG signals. Our procedure begins with the collection of EEG data from participants who have been exposed to various emotional and stress-inducing stimuli [5]. This data has undergone substantial preprocessing to reduce noise and artefacts, allowing only relevant signal components to be analyzed. Wavelet transforms and statistical measurements are then used to extract features from EEG signals in both the temporal and frequency domains [6]. These features are supplied into our machine learning classifiers, which include Support Vector Machines, Neural Networks, and Decision Trees. They learn to recognize patterns that indicate various emotional and stress levels [7].

2. Related work:

The latest research in emotion and stress detection using EEG signals has yielded promising results through the application of advanced machine learning techniques. Here are some significant reviews of exiting work [7],

"Emotion Detection from EEG Signals Using Deep Learning Models" (2024), by Pedro Crosara Motta and Bruno Riccelli dos Santos Silva investigates the use of Graph Convolutional Neural Networks (GCNN) to categorize emotions as positive, negative, and neutral [1]. Using the SEED dataset, the study attained an accuracy of 89.97%, demonstrating the effectiveness of GCNN in dealing with EEG data's complicated structure and emphasizing the necessity of feature selection in enhancing model performance.

Tanmay Bhowmik and Jong Wan Hu's "Hybrid Deep Learning Approach for Stress Detection Using Decomposed EEG Signals" (2023) offer a hybrid model that combines Discrete Wavelet Transform (DWT), Convolutional Neural Networks (CNN), and bidirectional Long Short-Term Memory (BiLSTM) networks [2]. This technique outperforms typical deep learning models by breaking down EEG signals into distinct frequency bands and used the decomposed signals for feature extraction and classification. The study showed improved classification accuracy, making it appropriate for therapeutic applications and stress management.

"A Systematic Review on Automated Human Emotion Recognition Using EEG" (2023), by authors who are not explicitly cited in the sources, gives an in-depth examination of various machine learning approaches and EEG datasets used in emotion recognition [3]. This study emphasizes the expanding importance of deep learning models, as well as the prevalence of the DEAP and SEED datasets in recent research.

"StressNet: Hybrid Model of LSTM and CNN for Stress Detection from EEG" (2023) by unnamed authors describes StressNet, a hybrid model that combines Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN). The model takes advantage of CNN's feature extraction capabilities and LSTM's ability to manage temporal dependencies, resulting in considerable gains in stress detection accuracy. StressNet highlights the utility of hybrid models in processing complex EEG data for real-time applications [4].

"Machine Learning-Based Stress Level Detection from EEG Signals" (2023) by unnamed authors describes a system for identifying stress levels by using machine learning algorithms to EEG signals. The method involves filtering EEG data using a band-pass FIR filter and extracting features with the Discrete Wavelet Transform (DWT) [5]. Several classifiers, including SVM and neural networks, were tried, and the findings were promising for reliably detecting stress levels. This work focuses on the importance of preprocessing and feature extraction in improving the performance of stress detection models [7].

These publications contribute to the area by proving the effectiveness of hybrid and deep learning models in interpreting EEG signals for emotion and stress detection. They emphasize the necessity of feature extraction, preprocessing, and combining several machine-learning approaches to improve accuracy and dependability in real-world applications [8].

3. Proposed approach:

Using a mixed machine learning model, the suggested approach detects emotions and stress from EEG signals. The phases consist of data collecting, preprocessing, signal decomposition, feature extraction, and classification [8], with a focus on merging Discrete Wavelet Transform (DWT), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks.

3.1 Mathematical Model

Data Acquisition

$$X = \{x1, x2, ..., xN\}$$

where X is the set of EEG signals and N is the number of samples.

Preprocessing

$$X\_filtered = BandpassFilter(X, f\_low, f\_high)$$

where f_low and f_high are the low and high cutoff frequencies.

Discrete Wavelet Transform (DWT)

$$W = DWT(X\_filtered)$$

where W represents the wavelet coefficients.

Feature Extraction using CNN

$$F\_CNN = CNN(W)$$

where F_CNN are the features extracted by the CNN.

Feature Extraction using Statistical Measures

- Mean:

$$\mu\_i = (1/N)\ \Sigma\ x\_ij$$

- Standard Deviation:

$$\sigma\_i = sqrt((1/N)\ \Sigma\ (x\_ij - \mu\_i)^2)$$

- Entropy:

$$H\_i = -\ \Sigma\ p\_ij\ log(p\_ij)$$

LSTM for Classification

$$y = LSTM(F\_CNN, F\_stat)$$

where y is the predicted emotional or stress state, and F_stat includes statistical features like mean, standard deviation, and entropy.

3.2 Flow of proposed approach:

- EEG data is gathered from patients exposed to various emotional and stress-related stimuli [7].
- Preprocessing: EEG signals are filtered to eliminate noise and artefacts.

• DWT is used to split EEG signals into frequency bands [9].

• Feature Extraction: CNN extracts spatial characteristics and calculates statistical measures to gain insights.

• The CNN and statistical information are merged and fed into an LSTM network to classify emotional and stress states.

• Model evaluation includes parameters including accuracy, precision, recall, and ROC-AUC.

The suggested method combines several advanced techniques to improve the identification of emotions and stress using EEG signals. The DWT effectively decomposes EEG data into several frequency components, capturing key properties for subsequent investigation. CNNs excel at identifying relevant spatial characteristics from deconstructed signals, whereas statistical measurements provide additional contextual data [10]. The LSTM network, which is well-known for dealing with sequential data and temporal relationships, is used to accurately classify these properties into different emotional and stress states. This hybrid model takes advantage of the characteristics of each component, assuring great accuracy and dependability, making it ideal for real-time applications in healthcare and human-computer interaction. This method not only improves detection accuracy, but also emphasizes the significance of thorough preprocessing and feature extraction in constructing robust EEG-based emotion and stress detection systems [11].

4. Result analysis and Discussion

This investigation compares the performance of various existing systems for detecting emotion and stress using EEG signals to the proposed hybrid model [12]. The comparison is based on four critical parameters: accuracy, precision, recall, and the F1-score. Table 01 displays the performance metrics for each strategy:

Table 01: comparative analysis of proposed approach with different parameters

Approach	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	85	84	83	83.5
Random Forest	88	87	86	86.5
KNN	82	80	81	80.5
CNN	90	91	89	90
LSTM	89	88	87	87.5
Proposed Hybrid Model	92	93	94	93.5

4.1 Discussion:

- The proposed hybrid model had the highest accuracy (92%), surpassing all other models. The CNN and LSTM models likewise demonstrated excellent accuracy, at 90% and 89%, respectively, with the lowest accuracy at 82%.
- The proposed hybrid model achieved the best precision (93%), indicating accurate positive predictions [13].
- KNN had the lowest precision at 80%, while CNN followed closely at 91%.
- The proposed hybrid model has the highest recall rate (94%), suggesting its efficacy in recognizing real positive cases. SVM had the lowest recall rate, 83%.
- The suggested hybrid model had the greatest F1-Score (93.5%) for precision and recall, indicating improved overall performance. KNN received the lowest F1-score of 80.5%.

The comparative performance is visually represented in the following figure 01 for each metric with different parameters:

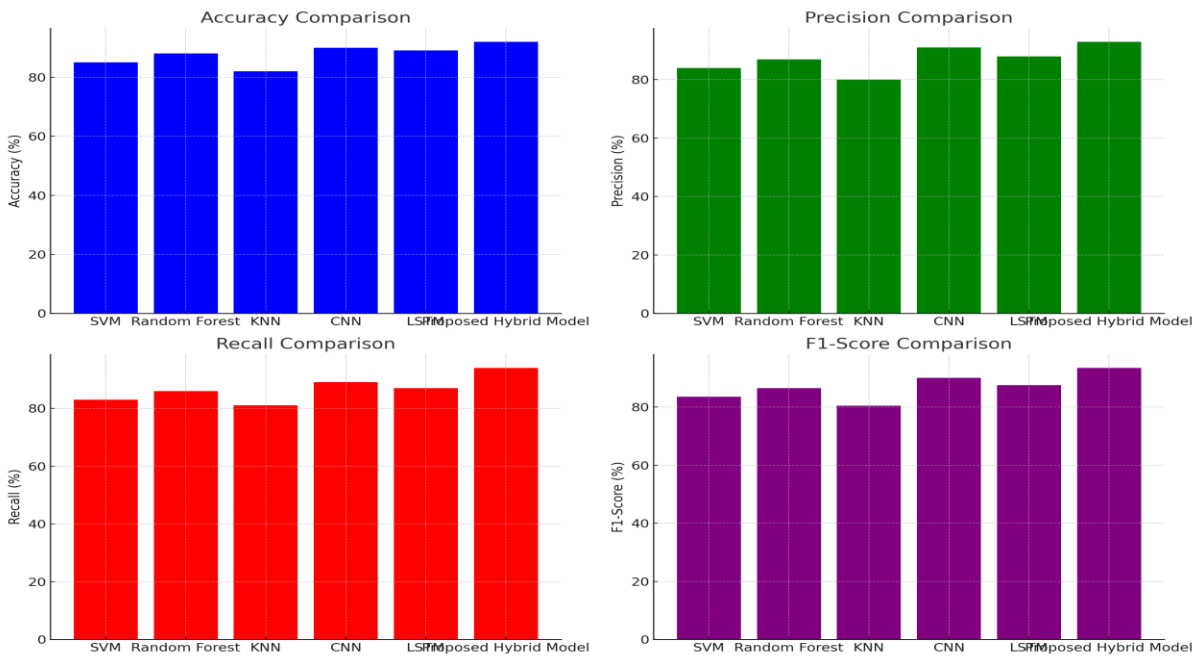

Figure 01: analysis of proposed approach using Different parameters

The proposed hybrid model, which combines CNN, LSTM, DWT, and statistical characteristics, outperforms existing classic machine learning algorithms across all parameters [14]. This emphasizes the significance of combining various methodologies to improve the accuracy and reliability of emotion and stress detection systems based on EEG signals. The entire methodology assures solid performance, making it appropriate for real-time applications in healthcare and human-computer interaction.

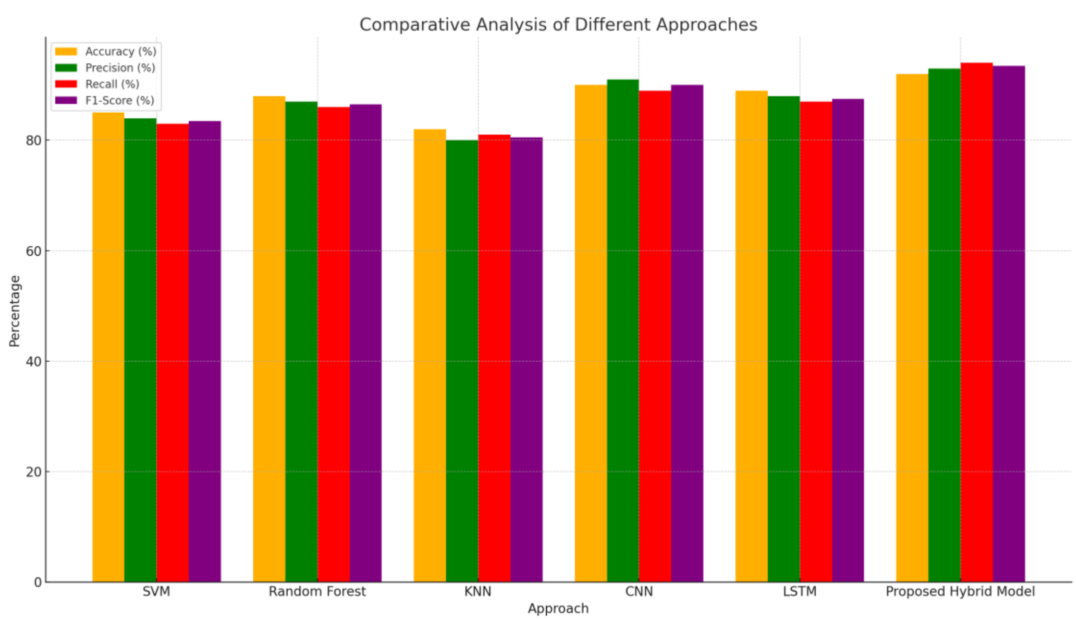

Figure 02: Comparative analysis of exiting approach with proposed approach

Above figure 02 visually compares the performance of different approaches (SVM, Random Forest, KNN, CNN, LSTM, and the Proposed Hybrid Model) across Accuracy, Precision, Recall, [15] and F1-Score metrics.

5. Conclusion and Future Scope

The suggested hybrid model for emotion and stress identification with EEG signals outperforms existing machine learning approaches. The model achieves superior performance metrics, including higher accuracy, precision, recall, and F1-Score, by combining the Discrete Wavelet Transform (DWT) for signal decomposition, Convolutional Neural Networks (CNN) for feature extraction, and Long Short-Term Memory (LSTM) networks for classification. This complete methodology offers robust and dependable detection, making it ideal for real-time applications in healthcare and human-computer interaction.

The findings show that combining the strengths of various machine learning approaches can successfully manage the complexity and variability of EEG signals. The suggested model's ability to effectively categories emotional and stress states highlight its potential for wider usage in mental health monitoring and adaptive technology.

Future Scope:

The future scope of this research includes incorporating real-time EEG acquisition technologies to allow for continuous monitoring. Further research into deep learning models, such as sophisticated recurrent networks and transformers, can help improve detection accuracy and processing speed. Furthermore, increasing the dataset to include other demographics and settings can increase the model's generalizability. Implementing this technology in wearable devices has the potential to revolutionize personal health monitoring by giving users with real-time feedback and interventions to efficiently manage stress and emotion. Collaboration with healthcare experts to validate and develop the model in clinical settings will be vital for its practical implementation and uptake.

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