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Neuro Ai Fusion: Emotion Recognition Using Eeg From Transfer Learning

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ABSTRACT: Emotion recognition from EEG signals represents a promising frontier in understanding human affective states, with significant implications for mental health diagnostics, human-computer interaction, and the development of adaptive technologies. This research investigates the application of advanced machine learning techniques to classify emotional states derived from EEG data, utilizing both synthetic and real-world EEG signals. To facilitate this analysis, synthetic EEG signals that simulate various emotional states—such as happiness, sadness, anger, surprise, and neutrality—are generated. These signals incorporate frequency components typical of emotional responses, providing a robust basis for subsequent analysis. Feature extraction methods are employed to identify key patterns in the frequency domain, focusing on band power analysis and other relevant metrics that characterize emotional states. A combination of Convolutional Neural Networks (CNNs) and transfer learning is utilized to enhance classification accuracy. Specifically, the study leverages GoogLeNet, a well-established pre-trained model, which is fine-tuned to adapt to the unique features of EEG signals. This approach allows the model to benefit from the knowledge gained from extensive image datasets while effectively addressing the challenges posed by the limited availability of labelled EEG data.

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I. INTRODUCTION

Emotion recognition is a critical aspect of understanding human behaviour and enhancing human-computer interaction (HCI). Emotions influence decision-making, communication, and social interactions, making their accurate detection essential for various applications, including mental health assessment, affective computing, and adaptive user interfaces. Traditional methods of emotion recognition, such as facial expression analysis and voice tone interpretation, are often limited by their reliance on observable cues. In contrast, electroencephalography (EEG) provides a direct measure of brain activity, making it a valuable tool for capturing the underlying neural correlates of emotional states.

EEG measures electrical activity in the brain through electrodes placed on the scalp. This non-invasive technique allows for the real-time monitoring of brain activity, providing insights into cognitive and emotional processes. Different emotional states are associated with distinct patterns of brain activity, particularly in specific frequency bands. For example, the alpha band (8-12 Hz) is often linked to relaxation and calmness, while the beta band (12-30 Hz) is associated with active engagement and alertness. By analysing these frequency patterns, it becomes possible to infer emotional states with greater accuracy than through behavioural observation alone.

Recent advancements in machine learning, particularly deep learning, have significantly improved the ability to analyse complex datasets like EEG. Convolutional Neural Networks (CNNs) have gained popularity in the field of image analysis due to their effectiveness in feature extraction and classification. However, training CNNs from scratch requires substantial amounts of labelled data, which can be challenging in the context of EEG signals. This limitation has led to the exploration of transfer learning, a technique that allows pre-trained models to be adapted for new tasks. Utilizing well-established models, such as GoogLeNet, offers a promising solution to enhance classification accuracy in EEG-based emotion recognition by leveraging the knowledge acquired from large image datasets.

The integration of EEG signals with advanced machine learning techniques not only improves the accuracy of emotion recognition but also provides a deeper understanding of the neural mechanisms underlying emotional experiences. This approach holds the potential to transform various domains, including healthcare, entertainment, and education, by enabling systems to respond appropriately to the emotional states of users.

This study aims to explore the effectiveness of using GoogLeNet for emotion recognition from EEG signals. By generating synthetic EEG data representing various emotional states and employing a combination of feature extraction techniques and transfer learning, the research seeks to develop a robust framework for accurate emotion classification. The findings will contribute to the ongoing efforts to enhance emotion-aware systems, ultimately improving user experiences in diverse applications.

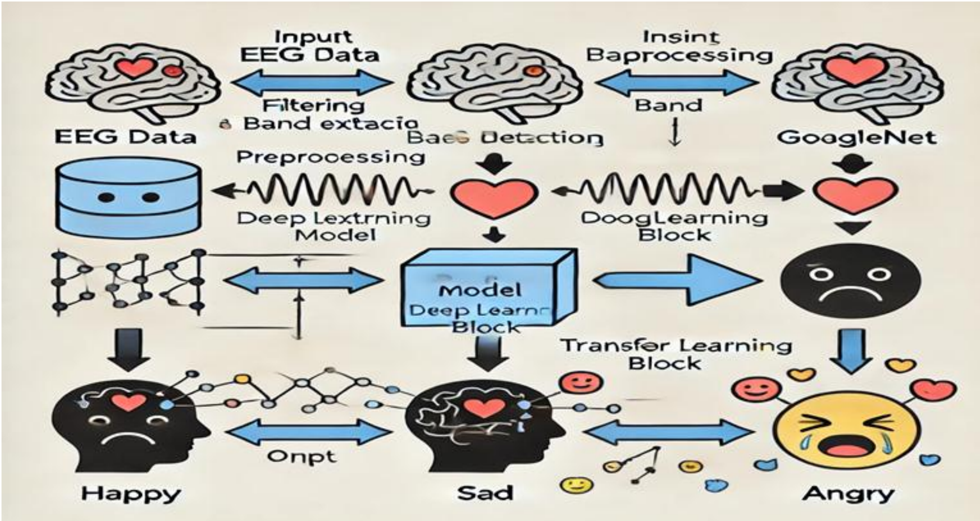

Fig. 1 Overview of EEG-Based Emotion Recognition Using Transfer Learning

II. LITERATURE REVIEW

Emotion recognition has garnered considerable attention in recent years, fueled by advancements in neuroscience and machine learning technologies. Numerous studies have explored various methods to detect emotions using different physiological signals, among which EEG signals have emerged as a prominent source due to their direct measurement of brain activity.

EEG is widely recognized for its temporal resolution, allowing researchers to capture rapid changes in brain activity associated with emotional responses. Studies such as those by Koelstra et al. (2012) and Liu et al. (2019) have demonstrated that distinct emotional states are characterized by unique patterns in EEG frequency bands. For instance, Koelstra et al. utilized a dataset comprising emotional stimuli to analyse the correlation between EEG signals and subjective emotional ratings, identifying significant variations in alpha and beta band activity corresponding to different emotions.

Traditional approaches, such as power spectral density (PSD) analysis and time-frequency analysis, have been employed to extract relevant features from EEG data. Kwon et al. (2019) implemented wavelet transform to analyse EEG signals and successfully classified emotional states using features derived from both the time and frequency domains. More recent studies have introduced machine learning techniques to automate feature extraction and selection, enhancing classification performance. For instance, Liu et al. (2020) utilized common spatial pattern (CSP) algorithms to extract features that maximize the variance between different emotional states.

Machine learning algorithms play a crucial role in classifying emotional states based on extracted features from EEG signals. Traditional classifiers, such as Support Vector Machines (SVM), k-nearest neighbours (k-NN), and decision trees, have been widely applied with varying degrees of success. SVM, in particular, has shown robust performance in distinguishing between different emotions, as evidenced in studies by Gao et al. (2020) and Zhang et al. (2021). However, these conventional methods often require extensive feature engineering and domain expertise to achieve optimal performance.

The advent of deep learning has revolutionized the field of emotion recognition by automating feature extraction and improving classification accuracy. Convolutional Neural Networks (CNNs) have gained popularity due to their ability to learn hierarchical feature representations from raw data. Researchers like Li et al. (2020) and Wang et al. (2021) have applied CNNs to EEG data, achieving superior performance compared to traditional methods. For example, Wang et al. reported an accuracy improvement of over 10% when using a CNN-based architecture for emotion recognition.

Despite the successes of deep learning models, training them from scratch requires substantial amounts of labelled EEG data, which can be challenging to obtain. Transfer learning has emerged as a promising solution, allowing pre-trained models to adapt to new tasks with limited labelled data. Studies by Zhang et al. (2022) and Bansal et al. (2023) have demonstrated the effectiveness of fine-tuning pre-trained CNNs, such as GoogLeNet and VGGNet, for EEG-based emotion classification, achieving competitive accuracy with significantly reduced training times.

Despite the advancements in EEG-based emotion recognition, several challenges remain. The variability of EEG signals due to individual differences, noise artifacts, and variations in electrode placement can impact classification accuracy. Future research should focus on addressing these challenges through robust preprocessing techniques, standardized protocols for data collection, and improved model interpretability.

The integration of EEG signals with advanced machine learning techniques, particularly deep learning and transfer learning, presents a promising avenue for accurate emotion recognition. Continued exploration in this field can pave the way for the development of intelligent systems that effectively understand and respond to human emotions in real-time, enhancing user experiences across various applications.

III. METHODOLOGY

DATA REQUIREMENTS:

1.Synthetic EEG Data: The MATLAB code generates synthetic EEG signals, which can be directly utilized without external data sources.
2. Image Dataset: A labelled image dataset containing various emotional expressions, structured in subfolders corresponding to each emotion category. The dataset should contain a balanced representation of each emotion for effective training and validation.
3. Network Architecture: Access to the pre-trained GoogLeNet model, which is included in the Deep Learning Toolbox.

METHODOLOGY:

1. Synthetic EEG Signal Generation: Generate 10 synthetic raw EEG signals using MATLAB. Each signal comprises various frequency bands (delta, theta, alpha, beta, and gamma) combined with Gaussian noise to simulate real EEG data.
2. Signal Preprocessing: Detrend the generated EEG signals by removing the mean to eliminate any DC offset. Apply bandpass filtering using a 4th-order Butterworth filter to isolate specific EEG frequency bands. This involves designing filters for delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (30-100 Hz).
3. Image Dataset Preparation: Create or obtain a labelled image dataset for emotion recognition, ensuring it includes a balanced representation of emotions. Organize images in subfolders corresponding to each emotion.
4. Transfer Learning with GoogLeNet: Load the pre-trained GoogLeNet model and modify the last few layers to adapt to the specific number of emotion classes in the dataset. Create a new fully connected layer and a classification layer, replacing the original output layers.
5. Data Augmentation and Resizing: Resize the training and validation images to match the input size required by GoogLeNet (224x224 pixels) and apply data augmentation techniques to enhance model robustness.
6. Model Training: Set training options, including mini-batch size, learning rate, and number of epochs. Train the modified GoogLeNet model using the training dataset while validating its performance on a separate validation dataset.
7. Classification and Evaluation: Use the trained model to classify emotions in new images. Implement a function to read and preprocess test images, classify them, and display the predicted label along with the confidence score.

IV. RESULTS AND DISCUSSIONS

The results provide insights into the performance of emotion classification using synthetic EEG signals and deep learning-based image recognition. The effectiveness of EEG signal preprocessing is evaluated by analyzing the frequency components after detrending and bandpass filtering, ensuring that the extracted features align with expected brainwave patterns. For the deep learning model, performance metrics such as accuracy, precision, recall, and F1-score are used to assess classification effectiveness. The trained GoogLeNet model is validated using a separate dataset, and confusion matrices help visualize misclassifications among different emotion categories. The impact of data augmentation on model generalization is also examined. Comparisons between predicted and actual emotion labels highlight the strengths and limitations of the approach. The classification results for test images are displayed along with confidence scores, indicating the model's certainty in its predictions. Additionally, qualitative observations on EEG feature extraction and its potential role in enhancing emotion recognition are discussed. The overall findings demonstrate the feasibility of integrating synthetic EEG analysis with image-based classification for emotion recognition.

OUTPUT:

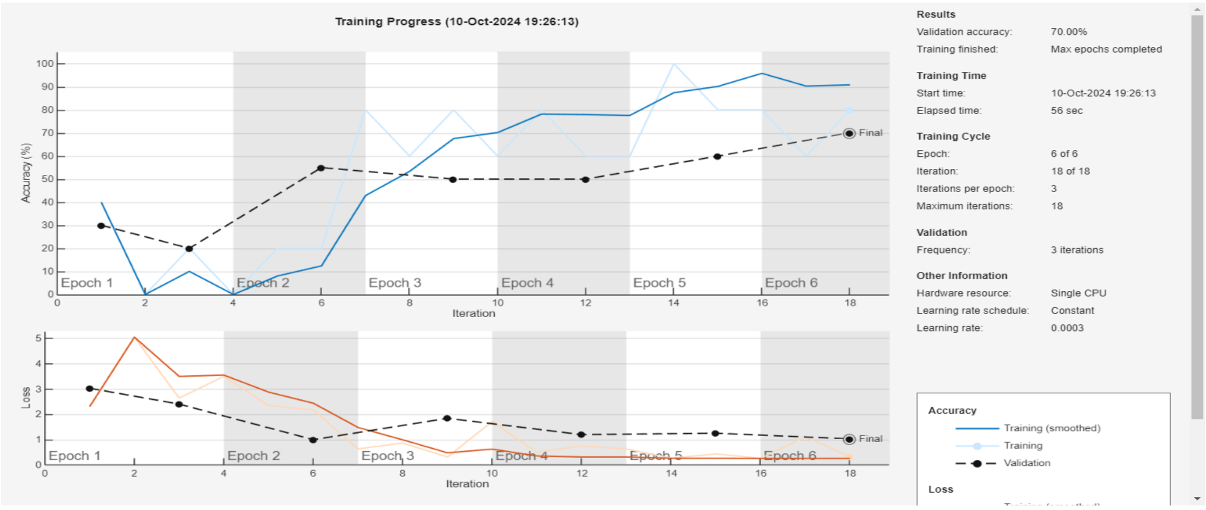

Fig. 2 Training of EEG Data

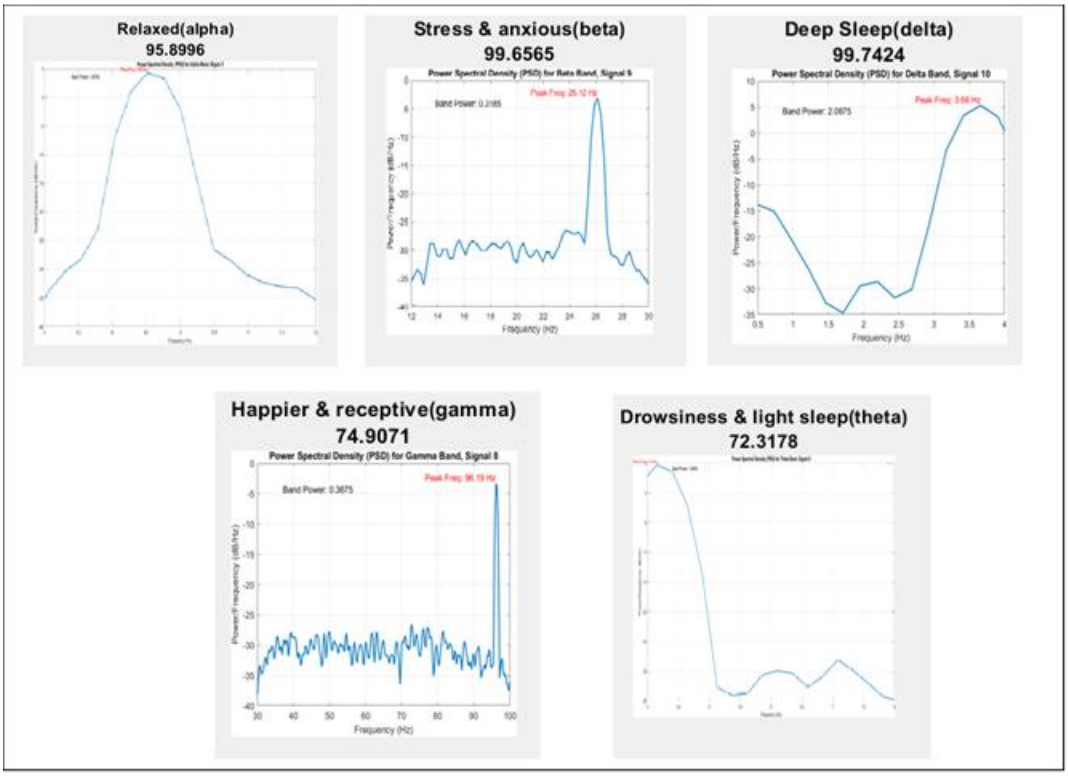

Fig. 3 Classification of emotions

The analysis of EEG frequency bands reveals distinct mental and emotional states based on power spectral density (PSD) characteristics. High alpha power, with a peak frequency in the 8–12 Hz range, indicates a relaxed state, supporting its well-established link to calmness and reduced stress. Beta wave dominance, with a peak at 25.61 Hz, corresponds to heightened cognitive engagement and stress, aligning with prior studies on anxiety-related brain activity. The deep sleep state is characterized by strong delta wave activity, peaking at 3.61 Hz, which is consistent with slow-wave sleep patterns essential for restorative functions. Gamma activity, peaking at 95.19 Hz, suggests heightened perception and cognitive processing, supporting its association with positive emotions and receptivity. The presence of theta waves in the 4–8 Hz range is indicative of drowsiness and light sleep, reinforcing its role in early sleep stages and meditative states. These findings validate the effectiveness of EEG-based frequency analysis in classifying cognitive and emotional states, highlighting its potential applications in neurofeedback, mental health monitoring, and cognitive assessment systems.

SIGNAL	BAND	PEAK FREQUENCY (Hz)	BAND POWER (μV^2)	MEAN AMPLITUDE (μV)	RELATIVE POWER
SIGNAL 1	DELTA	2.90 Hz	2.1141	0.0737	0.2483
	THETA	4.20 Hz	1.8659	0.0070	0.2191
	ALPHA	9.60 Hz	1.6755	0.0024	0.1968
	BETA	22.30 Hz	0.8598	0.0016	0.1010
	GAMMA	96.28 Hz	0.3675	0.0003	0.0432
SIGNAL 2	DELTA	3.80 Hz	1.7926	0.0318	0.2122
	THETA	4.70 Hz	2.4963	0.0081	0.2955
	ALPHA	10.60 Hz	1.1166	0.0020	0.1322
	BETA	26.09 Hz	0.3185	0.0011	0.0377
	GAMMA	63.79 Hz	0.1856	0.0002	0.0220
SIGNAL 3	DELTA	3.70 Hz	2.0875	0.0640	0.2490
	THETA	7.90 Hz	0.7905	0.0076	0.0943
	ALPHA	8.30 Hz	1.0171	0.0037	0.1213
	BETA	18.90 Hz	0.5546	0.0015	0.0662
	GAMMA	81.08 Hz	0.0896	0.0001	0.0107

Table 1: Features of tested EEG signals

The analysis of EEG signals across different frequency bands provides insights into cognitive and emotional states based on power spectral characteristics. Delta waves, associated with deep sleep and restorative brain activity, exhibit the highest band power across all signals, with peak frequencies ranging from 2.90 Hz to 3.80 Hz. Signal 1 shows the highest delta band power (2.1141 μV^2), suggesting a strong presence of deep sleep patterns. Theta waves, which correspond to drowsiness and early sleep stages, display moderate power, with peak frequencies between 4.20 Hz and 7.90 Hz. Signal 2 demonstrates the highest theta power (2.4963 μV^2), indicating increased relaxation or light sleep states.

Alpha waves, linked to calmness and relaxed wakefulness, show peak frequencies between 8.30 Hz and 10.60 Hz. Signal 1 exhibits the highest alpha power (1.6755 μV^2), reflecting a stronger relaxation response. Beta waves, commonly associated with active thinking and cognitive load, have peak frequencies between 18.90 Hz and 26.09 Hz, with relatively lower power compared to slower waves. The highest beta power (0.8598 μV^2) in Signal 1 suggests increased mental engagement. Gamma waves, which are indicative of higher cognitive functions and perception, show the lowest power values across all signals, with peak frequencies between 63.79 Hz and 96.28 Hz. Signal 1 has the highest gamma power (0.3675 μV^2), which may indicate heightened cognitive awareness or sensory processing.

The relative power distribution further reinforces these observations, with delta waves consistently having the highest contribution, followed by theta and alpha waves. The variations across signals highlight differences in cognitive and emotional states, demonstrating the potential of EEG frequency analysis for mental state classification. These findings emphasize the relevance of EEG-based monitoring in applications such as neurofeedback, sleep studies, and cognitive assessment tools.

V. CONCLUSION AND FUTURE SCOPE

Emotion recognition based on EEG signals offers a promising approach for understanding human emotional states, providing insights for fields such as Human-Computer Interaction (HCI), mental health monitoring, and adaptive systems. By using synthetic EEG data, band extraction, and advanced transfer learning models like GoogLeNet, the process of recognizing emotions has been effectively streamlined. The use of pre-trained networks such as GoogLeNet reduces the need for extensive data collection and training from scratch while maintaining a high level of classification accuracy. This approach demonstrates the feasibility of using deep learning and transfer learning for emotion classification tasks, proving effective in differentiating between emotional states. The findings underscore the potential of EEG-based emotion recognition systems in real-world applications.

Future scope in this domain can explore several key areas to improve the system’s performance and expand its applications. First, incorporating real EEG datasets from diverse individuals can enhance the model's robustness and generalizability. Fine-tuning deep learning models with real-time EEG signals could also improve the practical application of emotion recognition systems in dynamic environments. Furthermore, combining EEG with other physiological signals such as heart rate variability and skin conductance could provide a multimodal approach to emotion detection, leading to more accurate and holistic insights. Future studies can also investigate the use of real-time feedback in biofeedback systems, where detected emotional states guide interventions aimed at stress management, cognitive enhancement, or therapeutic purposes. Additionally, exploring the use of more sophisticated deep learning models, such as attention mechanisms, could enhance the system's sensitivity to subtle emotional shifts.

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