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EMOTION DETECTION USING EEG SIGNALS: A SUMMARY

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Abstract

Emotion detection using electroencephalogram (EEG) signals offers a groundbreaking approach to analyzing brainwaves and identifying emotional states such as happiness, sadness, and anger. By non-invasively recording electrical brain activity, EEG enables real-time study of emotions with significant applications across healthcare, marketing, education, and human-computer interaction. In marketing, EEG-based tools help businesses analyze consumer reactions to create personalized strategies. In healthcare, this technology supports mental health diagnosis and tailored therapy by providing dynamic insights into patients' emotions. EEG systems also enhance human-computer interaction, enabling adaptive interfaces that respond to user' emotional states. Integrating EEG with virtual reality (VR) further expands its potential, creating immersive environments for gaming, therapy, and training that adjust dynamically to emotions. These advancements bridge neuroscience and technology, driving innovation in affective computing. The adaptability and real-time capabilities of EEG-based emotion detection systems underscore their transformative role in developing emotionally intelligent technologies. They offer continuous emotion monitoring, advancing our understanding of emotional dynamics and improving user experiences across domains. As this field progresses, EEG-based emotion recognition is poised to revolutionize interactions, fostering systems that meaningfully respond to human emotions.

I. Introduction

The research paper, Emotion Detection Using EEG Signals," explores how electroencephalography (EEG) can be applied to identify human emotional states [1]. Emotions play a vital role in human cognition, affecting decision-making, perception, and interactions [2]. This study uses EEG, a noninvasive technique that measures electrical brain activity, to monitor cognitive and emotional processes [3]. Through EEG-based emotion detection, researchers can track emotional states in real time, which holds potential applications in healthcare for mental health diagnosis, in marketing for understanding consumer reactions, and in human-computer interactions for personalized experiences [4].

The main challenge in EEG-based emotion detection is processing complex brainwave data with noise, variability between subjects, and the intricate nature of non-linear patterns [5]. Traditional machine learning models like Support Vector Machines (SVM) and Random Forests have been utilized but faced limitations in accuracy and feature engineering requirements [6]. Deep learning models, such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN), show promise in addressing these challenges by extracting spatial and temporal dependencies in EEG signals, enhancing accuracy and robustness [7]. This research focuses on optimizing these models for emotion recognition, aiming to create more efficient, real-time emotion detection systems [8].

A. Problem

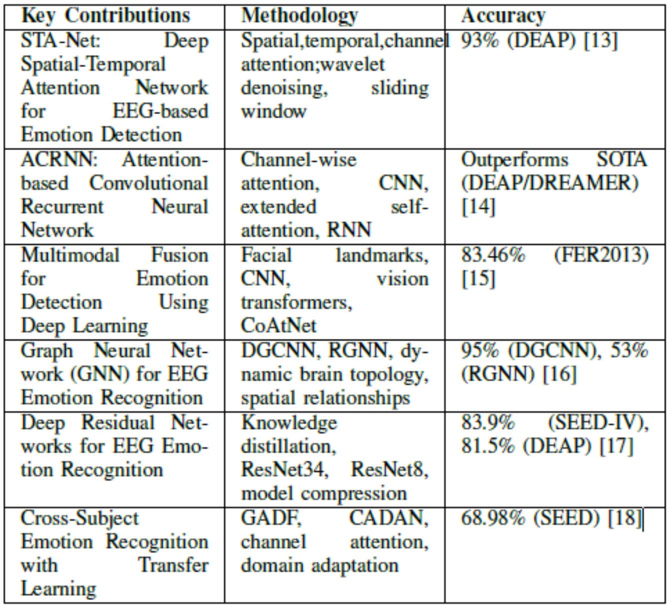
The project seeks to develop an efficient and accurate model for detecting emotions based on EEG signals. The main issues to address include achieving high classification accuracy in real-time, handling cross-subject variability, and reducing computational requirements for practical applications. By exploring and comparing different deep learning architectures, the study aims to improve EEG-based emotion detection models' applicability in diverse fields such as healthcare and marketing.

II. Literature Review

Recent advancements in EEG-based emotion recognition have leveraged cutting-edge datasets, neural networks, and innovative methodologies to analyze emotional states such as arousal, valence, and dominance [9] – [12]. Techniques like frequency band extraction, Power Spectrum Density analysis, and deep learning models such as Bi-LSTM and GRU have shown significant accuracy, with GRU+Bi-LSTM excelling in binary classification and Bi-LSTM in multiclass classification [11]. Research also focuses on optimizing brain-computer interfaces by refining electrode placement and simplifying systems for wearable devices [12]. Advanced neural architectures, including spatial-temporal attention networks and multimodal frameworks, integrate EEG signals with other modalities like facial landmarks, achieving high accuracy across datasets [13] – [24]. These innovations pave the way for applications in mental health monitoring, stress management, real-time human-computer interaction, and affective computing, emphasizing the potential of EEG systems in both clinical and nonclinical settings [9] – [12].

Emotion recognition using EEG signals has emerged as a transformative research field, utilizing advanced datasets, machine learning models, and innovative techniques [9]. One study explores the detection of emotional states such as arousal, valence, dominance, and liking using EEG data processed through frequency band extraction and Power Spectrum Density analysis [10]. Deep learning models like Bi-LSTM and GRU are compared, with the GRU+Bi-LSTM combination achieving high accuracy in binary classification and Bi-LSTM performing well in multiclass classification [11]. Another approach focuses on improving brain-computer interfaces (BCIs) by optimizing electrode placement, reducing complexity while maintaining high accuracy, and paving the way for wearable emotion-detection devices [12].

Table I. Key contributions, methodology, and accuracy in EEG-based emotion detection studies



Key Contributions	Methodology	Accuracy
STA-Net: Deep Spatial-Temporal Attention Network for EEG-based Emotion Detection	Spatial,temporal,channel attention;wavelet denoising, sliding window	93% (DEAP) [13]
ACRNN: Attention-based Convolutional Recurrent Neural Network	Channel-wise attention, CNN, extended self-attention, RNN	Outperforms SOTA (DEAP/DREAMER) [14]
Multimodal Fusion for Emotion Detection Using Deep Learning	Facial landmarks, CNN, vision transformers, CoAtNet	83.46% (FER2013) [15]
Graph Neural Network (GNN) for EEG Emotion Recognition	DGCNN, RGNN, dynamic brain topology, spatial relationships	95% (DGCNN), 53% (RGNN) [16]
Deep Residual Networks for EEG Emotion Recognition	Knowledge distillation, ResNet34, ResNet8, model compression	83.9% (SEED-IV), 81.5% (DEAP) [17]
Cross-Subject Emotion Recognition with Transfer Learning	GADF, CADAN, channel attention, domain adaptation	68.98% (SEED) [18]

The potential of EEG for mental health and stress management is equally promising. By tracking brain activity and emotional processes, EEG systems facilitate early diagnosis of mental health disorders and enable personalized treatment plans. Advanced models for stress detection leverage datasets to analyze patterns in EEG signals, with neural networks outperforming traditional machine learning methods in identifying arousal and valence states. These advancements contribute to enhanced mental health monitoring systems, enabling timely interventions, and improving overall well-being.

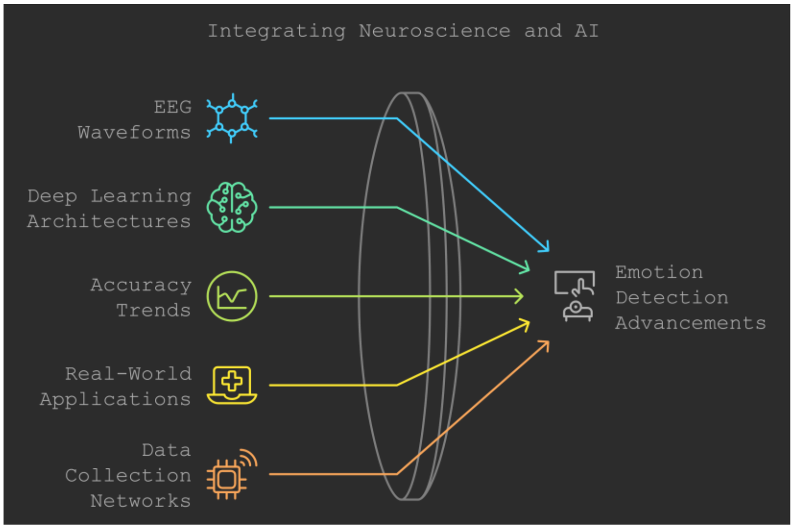


Fig. 1. Advancements in EEG-based emotion detection: Bridging neuroscience and AI for real-time applications in healthcare, marketing, and human-computer interaction.

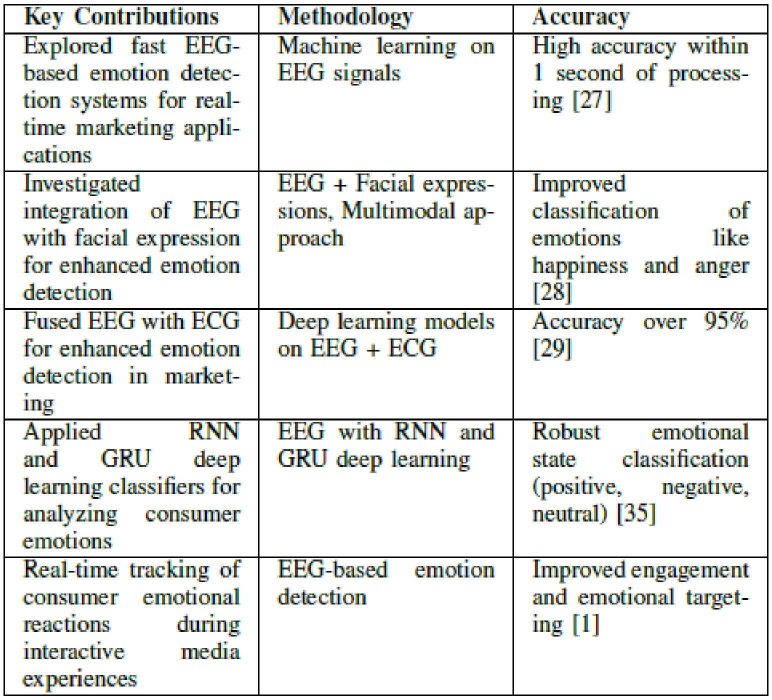
Innovations in neural networks and preprocessing techniques have significantly advanced EEG-based emotion classification [13]. A two-stream Bi-Hemispheric neural network has shown promising results in classifying emotions by analyzing critical temporal intervals in EEG signals [19]. Another method, using a Deep Spatial-Temporal Attention Network, enhances feature extraction by preserving both temporal and frequency characteristics [20]. These models demonstrate high accuracy and outperform traditional methods, showcasing the capability of EEG systems in detailed emotional analysis [21].

Multimodal frameworks further enhance emotion recognition. Advanced frameworks utilizing multivariate decomposition methods analyze rhythm-specific features in EEG signals, achieving high classification accuracy across emotional states [22]. These methods emphasize the importance of beta and gamma rhythms and employ diverse, multilingual participant databases for robustness [23]. By combining artifact resistance with efficient processing, these systems highlight the potential for EEG integration in broader applications, from affective computing to real-time human-computer interaction [24].

Emotion detection using EEG signals has revolutionized marketing by enabling real-time analysis of consumer emotions, enhancing personalized and emotionally resonant strategies [25], [26]. Rapid detection techniques, such as asymmetric spatial filtering of 1-second EEG segments, deliver high classification accuracy for arousal and valence, ideal for real-time applications [27]. Multimodal approaches, including EEG integration with facial expressions, ECG, and VR settings, have significantly improved emotion recognition accuracy, achieving up to 95.07% with advanced models like LSTM-MLP and CNN [28]–[30]. These systems are particularly impactful in creating immersive and targeted marketing campaigns by leveraging real-time emotional feedback [1], [31]. Addressing data scarcity through synthetic EEG data generation with diffusion models further enhances classifier accuracy, ensuring robust performance even with limited datasets [32], [33]. These innovations underscore the transformative potential of EEG-based emotion detection in delivering emotionally engaging and effective consumer experiences [34].

1) Member 2 (Yogitha Devarapally): Emotion detection using EEG signals has demonstrated immense potential in marketing by enabling real-time analysis of consumer emotions during product testing or advertisements [25]. Studies highlight the value of analyzing consumer brain activity to predict emotional reactions, which can lead to personalized and emotionally resonant marketing strategies [26]. Fast emotion detection methods utilize asymmetric spatial filtering to process 1-second EEG segments, achieving high accuracy in classifying arousal and valence. These rapid detection systems are ideal for real-time applications, providing businesses with actionable insights into consumer responses [27].

Table II. Notable contributions, techniques, and performance metrics in EEG-based emotion recognition research



Key Contributions	Methodology	Accuracy
Explored fast EEG-based emotion detection systems for real-time marketing applications	Machine learning on EEG signals	High accuracy within 1 second of processing [27]
Investigated integration of EEG with facial expression for enhanced emotion detection	EEG + Facial expressions, Multimodal approach	Improved classification of emotions like happiness and anger [28]
Fused EEG with ECG for enhanced emotion detection in marketing	Deep learning models on EEG + ECG	Accuracy over 95% [29]
Applied RNN and GRU deep learning classifiers for analyzing consumer emotions	EEG with RNN and GRU deep learning	Robust emotional state classification (positive, negative, neutral) [35]
Real-time tracking of consumer emotional reactions during interactive media experiences	EEG-based emotion detection	Improved engagement and emotional targeting [1]

Integrating multiple modalities has further improved emotion recognition accuracy [36]. For instance, combining EEG and facial expression data achieved higher classification accuracy by leveraging deep learning and optimizing electrode placement [37]. Similarly, the fusion of single-lead EEG and ECG signals, utilizing models such as LSTM-MLP and CNN, achieved up to 95.07% accuracy. These approaches are particularly relevant to marketing, where multimodal systems offer a more comprehensive understanding of consumer emotions, enabling the development of targeted advertising strategies [38].

EEG-based systems have also been applied in innovative environments such as virtual reality (VR) [30]. Studies demonstrated the use of EEG signals to gauge emotional reactions in VR settings, achieving up to 90.20% accuracy using SVM classifiers. Such methodologies are instrumental in creating immersive marketing campaigns, where real-time emotional feedback can enhance the personalization of VR advertisements [31]. Similarly, combining EEG, ECG, and acoustic signals offered a scalable approach for understanding consumer emotional engagement in dynamic environments [30].

To address challenges like data scarcity, synthetic EEG data generated by diffusion models has been proposed to enhance classifier accuracy [32]. By integrating synthetic and real EEG data, this method improves emotion recognition systems, particularly in marketing scenarios where understanding nuanced consumer emotions is essential [29]. Furthermore, a comprehensive review of deep learning models emphasized the reliability of EEG for capturing authentic emotional data [33]. These advancements underscore the transformative role of EEG-based emotion detection in marketing, enabling brands to create more emotionally engaging and effective consumer experiences [34].

(a) Epoc+ and the position of 14 electrodes (b) Smart glasses and the position of 9 sensors (c) HRM strap (d) Kinect and its output

Fig. 2. Devices and techniques for emotion recognition (a) EEG headset and electrode layout for brainwave signal collection. (b) Facial mapping and landmark detection for emotion analysis. (c) HRM strap used for physiological monitoring. (d) Kinect device and its output for capturing body movements and depth images [29].

Hardware-based EEG emotion classification systems have demonstrated significant potential for wearable devices, leveraging Fast Fourier Transform (FFT) and Support Vector Machine (SVM) to classify emotions with an average accuracy of 78.11% and emphasizing low power consumption and hardware efficiency [39]. Advanced models like DSSTNet, integrating spatial, spectral, and temporal features through graph convolutional networks (GCNs), achieve 95.45% accuracy, showcasing robustness in emotion classification [4]. Multimodal approaches, combining EEG with ECG signals, enhance accuracy to 98.11% for emotional states such as happiness and sadness, emphasizing their utility in real-time affective brain-computer interfaces [40]. Deep learning models, including Bi-LSTM and GRU, achieve up to 96.53% accuracy in binary emotion classification, further advancing EEG's role in real-time systems [41]. FPGA-based implementations, offering up to 90% accuracy, highlight practical solutions for healthcare and human-computer interaction with low latency and resource utilization [42]. Additionally, EEG systems paired with facial recognition enhance diagnostic tools for neurological disorders and stress detection, supported by CNN architectures and transfer learning models [5]. EEG's versatility also extends to critical thinking assessment, stress detection, and biometric identification, underlining its potential across diverse domains [35], [43].

The use of hardware-based EEG emotion classification systems has shown great potential for wearable devices. These systems process EEG signals using Fast Fourier Transform (FFT) and classify emotions with Support Vector Machine (SVM), achieving an average accuracy of 78.11%. Implemented on FPGA platforms, such designs emphasize low-power consumption and reduced hardware complexity, making them suitable for real-time, portable emotion detection systems [39]. Similarly, DSSTNet, a multi-channel EEG recognition system, integrates spatial, spectral, and temporal features using graph convolutional networks (GCNs). By transforming EEG signals into graph-structured data and incorporating band attention modules, this system achieves 95.45% accuracy, demonstrating robustness and precision in emotion classification [4].

Multimodal approaches further enhance emotion detection accuracy by combining EEG with other physiological signals. The fusion of EEG and ECG signals has achieved high classification accuracy, with systems recording up to 98.11% when classifying emotions such as happiness and sadness. These results underscore the value of combining multiple modalities to improve emotion recognition, particularly for applications in real-time affective brain-computer interfaces (aBCIs) [40]. Similarly, leveraging advanced deep learning models like Bi-LSTM and GRU has shown promising outcomes for classifying emotional states. By extracting features such as Power Spectrum Density (PSD) from EEG data, these systems achieve up to 96.53% accuracy in binary classification tasks [41].

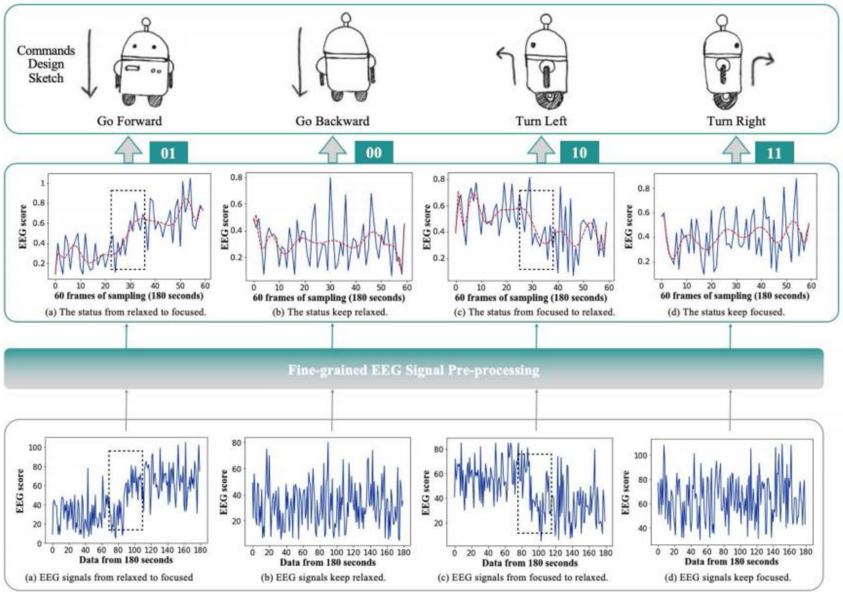


Fig. 3. EEG-based emotion detection and signal processing workflow [5].

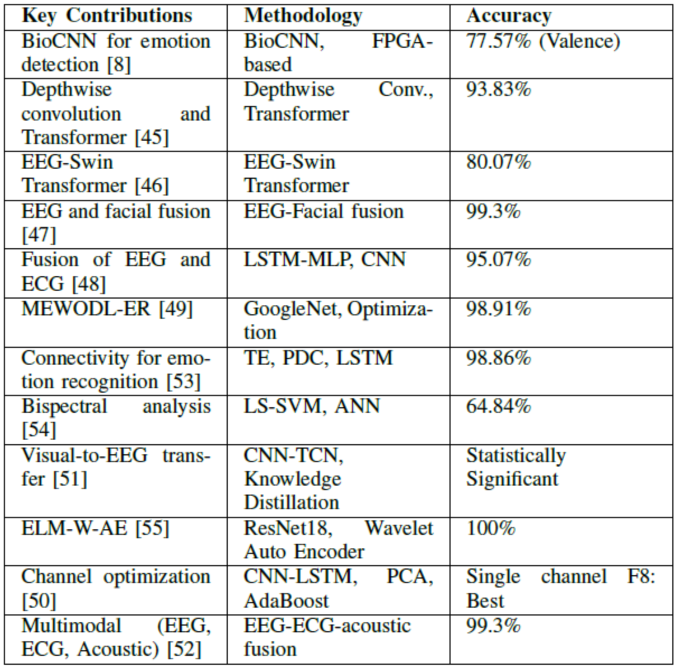
Table III. Core contributions, techniques, and performance metrics in EEG-based emotion recognition research

Key Contributions	Methodology	Accuracy
Hardware-based EEG emotion classification optimized for wearables [39].	SVM + FFT	78.11%
FPGA-based EEG system for real-time emotion detection with low power usage [42].	FPGA-based system	90%
Predictive healthcare system using EEG and facial emotion recognition [?].	CNN architectures + transfer learning	91.83%
Emotion classification using Bi-LSTM and GRU models for EEG data [41].	GRU + Bi-LSTM	96.53%
Multimodal approach combining EEG and ECG for emotion classification [40].	EEG + ECG	98.11%
Hybrid deep learning model combining EEG, ECG, and GSR [?].	EEG + ECG + GSR	98.2%

Real-time emotion detection systems implemented on FPGA technology offer practical solutions for healthcare and human-computer interaction. These systems integrate EEG data acquisition, preprocessing, and classification to classify emotions with up to 90% accuracy while maintaining low latency and resource utilization. Such advancements highlight the potential for wearable devices in emotion detection applications [42]. Moreover, combining EEG and facial recognition has proven effective for diagnosing neurological disorders and enhancing personalized healthcare. These systems, supported by deep learning and transfer learning models, report high accuracies, emphasizing their relevance in early diagnosis and treatment personalization [44].

EEG-based emotion recognition also contributes to areas like critical thinking assessment, stress detection, and biometric identification. By combining EEG with facial recognition and employing chaos theory descriptors, systems can evaluate cognitive states and enhance educational tools [43]. For stress detection, CNN-based deep learning models effectively classify stress levels despite challenges like noise and data imbalances [5]. EEG signals also offer a secure and nonintrusive biometric feature, achieving high identification accuracy by focusing on distinctive brain signal patterns in the frontal and parieto-occipital regions [35]. These advancements highlight the versatility and transformative potential of EEG-based technologies across diverse domains.

Table IV. This table summarizes significant advancements in EEG-based emotion recognition



Key Contributions	Methodology	Accuracy
BioCNN for emotion detection [8]	BioCNN, FPGA-based	77.57% (Valence)
Depthwise convolution and Transformer [45]	Depthwise Conv., Transformer	93.83%
EEG-Swin Transformer [46]	EEG-Swin Transformer	80.07%
EEG and facial fusion [47]	EEG-Facial fusion	99.3%
Fusion of EEG and ECG [48]	LSTM-MLP, CNN	95.07%
MEWODL-ER [49]	GoogleNet, Optimization	98.91%
Connectivity for emotion recognition [53]	TE, PDC, LSTM	98.86%
Bispectral analysis [54]	LS-SVM, ANN	64.84%
Visual-to-EEG transfer [51]	CNN-TCN, Knowledge Distillation	Statistically Significant
ELM-W-AE [55]	ResNet18, Wavelet Auto Encoder	100%
Channel optimization [50]	CNN-LSTM, PCA, AdaBoost	Single channel F8: Best
Multimodal (EEG, ECG, Acoustic) [52]	EEG-ECG-acoustic fusion	99.3%

The field of EEG-based emotion recognition has made significant strides with methodologies tailored for real-time and high-accuracy applications. Innovations such as BioCNN, which achieves 77.57% accuracy for valence and is optimized for energy efficiency (11 GOps/W), highlight the potential for wearable applications [8]. Advanced architectures like depth wise convolution and Transformer encoders in the DCoT model achieve subject-dependent accuracy of 93.83% on the SEED dataset [45], while EEG-Swin Transformers improve feature extraction for subject-independent scenarios [46]. Hybrid techniques, such as combining EEG with ECG or facial recognition, have achieved accuracies of up to 99.3%, emphasizing the effectiveness of multimodal systems in healthcare and real-time emotion detection [47], [48]. Deep learning innovations like MEWODL-ER and quantum autoencoders have shown robust performance, with accuracies exceeding 98.91%, driven by advanced feature extraction and optimization methods [49]. Future research focuses on reducing computational complexity, channel optimization, and integrating multimodal and knowledge transfer approaches to create scalable, interpretable systems applicable in therapy, education, and entertainment [50] – [52].

The field of EEG-based emotion recognition has seen significant advancements through innovative methodologies and architectures tailored for real-time and high-accuracy applications. For instance, BioCNN, a Convolutional Neural Network designed for emotion detection in neurological patients, achieved notable accuracies of 77.57% for valence and 71.25% for arousal on datasets such as DEAP and DREAMER, showcasing its suitability for wearable applications due to its energy efficiency (11 GOps/W) [8]. Other notable approaches include the use of depth wise convolution and Transformer encoders in the DCoT model, achieving subject-dependent accuracy of 93.83% on the SEED dataset [45], and EEG spectral images (ESI) combined with Swin Transformers, which enhanced feature extraction for subject-independent scenarios with significant improvements over baseline models [46].

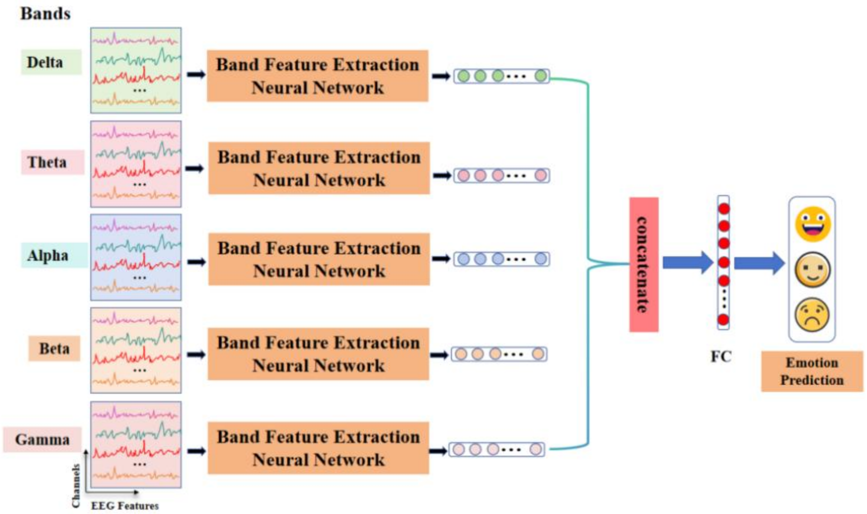


Fig. 4. Schematic diagram of the architecture of an emotional network based on EEG frequency bands. The input of the network is the feature of five frequency bands [50].

Hybrid and multimodal techniques have further propelled the field. For example, methods combining EEG with ECG or facial recognition have demonstrated superior accuracies, such as 99.3% in a real-time multimodal system for recognizing emotions in healthcare applications [47]. The fusion of features such as wavelet energy entropy, power spectrum, and effective connectivity (EC) has also shown promise, with models like LSTM-MLP and CNN-LSTM achieving accuracies exceeding 95% [48]. These approaches underscore the effectiveness of leveraging multiple physiological signals or combining traditional feature extraction with advanced classifiers like XGBoost and ResNet18, ensuring better generalization for real-world use cases [53].

Several studies emphasize the potential of machine learning and deep learning techniques in emotion recognition. Models such as Modified Earthworm Optimization with Deep Learning Assisted Emotion Recognition (MEWODL-ER) and quantum autoencoders have achieved impressive accuracies of 98.91% and higher, indicating their robust performance in Human-Computer Interaction (HCI) applications [49]. Additionally, innovations like bispectral analysis [54], chaotic descriptors [56], and new data augmentation techniques such as Extreme Learning Machine Wavelet Auto Encoder (ELM-WAE) have improved the granularity of emotion classification, demonstrating a 20% accuracy improvement on challenging datasets like GAMEEMO [55].

Future directions in EEG-based emotion recognition focus on reducing computational complexity while improving interpretability and domain adaptation. Research exploring channel selection strategies, such as focusing on key EEG channels like FT7 and F8, has proven effective in lowering equipment and computational costs without sacrificing accuracy [50]. Studies integrating visual-to-EEG knowledge transfer [51] or multimodal approaches combining EEG and acoustic signals highlight the growing interest in creating scalable, interpretable systems for diverse applications, from mood disorder therapy to enhancing user experiences in entertainment and education [52].

III. Our approach

Our proposed approach for emotion detection using EEG signals introduces a novel multimodal system that combines EEG signals with facial expressions to enhance classification accuracy and facilitate real-time applications [39]. The methodology begins with advanced signal preprocessing techniques, such as wavelet transforms for noise reduction and temporal segmentation for extracting relevant time-window features, ensuring clean and meaningful data for analysis [6]. By integrating EEG signals with facial expression data at the feature level, our system leverages the power of deep learning models to fuse Power Spectrum Density (PSD) features from EEG and spatial landmark features from facial expressions [57].

The core of the proposed system is a hybrid deep learning architecture that combines a Transformer Encoder for capturing spatial relationships across EEG channels and an LSTM Decoder to model temporal dependencies in emotion transitions [8]. Parallel to this, a Convolutional Neural Network (CNN) processes facial expression data, and the features are fused to form a comprehensive representation of emotional states [58]. Furthermore, we optimize hardware complexity by dynamically selecting key electrode channels, such as F8 and FT7, to minimize the number of electrodes required while maintaining high classification accuracy. For real-time adaptation, the system is designed with a lightweight architecture suitable for wearable devices, ensuring practical implementation on platforms like FPGA or mobile processors [47].

To validate the approach, we use benchmark datasets such as SEED and DEAP for cross-subject evaluation [59]. Preprocessing steps include normalization of EEG signals across subjects and data augmentation techniques such as time-shifting and Gaussian noise addition [60]. Training employs transfer learning to improve model generalization across diverse populations, with performance evaluated through metrics like accuracy, F1 score, and latency [61]. This comprehensive approach combines cutting-edge techniques in signal processing, deep learning, and hardware optimization, paving the way for real-world, multimodal emotion detection systems [36].

IV. Methodology

The methodology for this study on emotion detection using EEG signals involves a structured approach beginning with data acquisition and preprocessing [42]. EEG data is sourced from well-established datasets, such as DEAP, which provide labeled emotional states across multiple participants, focusing on metrics like arousal and valence [62]. The initial step involves preprocessing the raw EEG signals to reduce noise and artifacts that can distort the data. Techniques such as wavelet denoising are employed to ensure signal clarity, while Fast Fourier Transform (FFT) is used to convert the signals into frequency-domain features [54]. This transformation allows for the analysis of specific brainwave frequencies (e.g., alpha, beta), which have been shown to correlate with emotional states [38]. Through these preprocessing and feature extraction steps, the study ensures a high-quality data foundation for subsequent analysis [63].

The study then applies deep learning models—specifically, Bi-LSTM (Bidirectional Long Short-Term Memory) and GRU (Gated Recurrent Unit) networks—to classify emotions based on the extracted EEG features [13]. These models are particularly well-suited for EEG data due to their capacity to capture temporal dependencies, making them effective for recognizing patterns that span across time within the EEG signals [34]. The models are trained and fine-tuned with hyperparameters optimized for EEG data, enhancing their classification accuracy and robustness. Performance is evaluated using metrics such as accuracy, precision, recall, and F1 score, with additional testing in real-time conditions to assess the models' efficacy with reduced electrode configurations [32]. This comprehensive methodology aims to develop a practical, high-performing emotion detection model that can operate effectively in diverse real-world scenarios [3].

V. Potential impact on society

The proposed multimodal emotion detection system has the potential to make significant contributions to society by addressing critical challenges in healthcare, marketing, education, and human-computer interaction [10]. In healthcare, the system could revolutionize mental health diagnosis by identifying emotional states such as stress, anxiety, and depression through non-invasive monitoring [36]. Personalized therapy sessions could be enhanced by adapting treatment plans based on real-time emotional feedback, offering better outcomes for patients. Similarly, the system could support stress management programs by detecting and intervening during high-stress periods [31].

In marketing, this technology can enable companies to gain deeper insights into consumer reactions during product testing and advertising campaigns [30]. By leveraging real-time emotion detection, marketers could craft emotionally engaging content and optimize user experiences on digital platforms [31]. For the education sector, the system could monitor Students' emotional states during online learning sessions, ensuring better engagement by tailoring educational content and detecting cognitive overload. This could significantly improve learning outcomes and student satisfaction [9].

In human-computer interaction, the system can facilitate adaptive environments, such as gaming and virtual reality platforms, that respond to users' emotional states [64]. This could also extend to accessibility solutions for individuals with cognitive or emotional disabilities, enabling a more inclusive digital experience [34]. Additionally, the integration of emotion detection in wearable devices has immense potential for continuous mood monitoring, helping individuals maintain productivity and emotional well-being [34].

VI. Results

The results of this study demonstrate the efficacy of Bi-LSTM and GRU models in accurately classifying emotional states based on EEG signals [8]. The GRU model achieved a notable peak accuracy of 96.53% for binary classification tasks, while the Bi-LSTM model yielded an accuracy of 92.36% for multi-class classification, signifying its robustness across multiple emotional states [36]. Key performance metrics —accuracy, precision, recall, and F1 score—were recorded for each model to provide a comprehensive evaluation of their classification capabilities [65]. Furthermore, both models were tested under conditions simulating real-time applications, which involved reducing the number of electrodes [4]. These real-time tests showed that accuracy remained high even with fewer electrodes, underscoring the practicality of a reduced configuration for wearable EEG devices [50]. These findings collectively illustrate the potential of deep learning models to provide reliable and accurate emotion classification in both controlled and real-time settings [26].

VII. Discussion

The study's findings underscore the advantages of using deep learning models, specifically Bi-LSTM and GRU, for EEG-based emotion detection [4]. Traditional machine learning methods often require extensive manual feature engineering and are limited in capturing the complex temporal dependencies of EEG data [56]. In contrast, the deep learning models implemented in this study demonstrated superior performance by effectively learning patterns within the EEG signals that correspond to different emotional states [50]. The results indicate that even with reduced electrode configurations, the models maintained high classification accuracy, suggesting that compact, wearable devices could support real-time emotion detection applications.

However, certain challenges persist, notably cross-subject variability and the computational resources required for real-time processing [54]. These challenges highlight the need for further model optimization to enhance generalizability and efficiency, especially in scenarios requiring rapid, real-time emotion classification [27]. The results also suggest promising applications in healthcare, marketing, and human-computer interaction, where real-time emotion detection could enable more personalized and emotionally adaptive systems [2].

VIII. Future works

Building on the insights gained from this study, future research will explore several avenues to enhance EEG-based emotion detection systems. One potential direction is the integration of multimodal data sources, such as combining EEG with other physiological signals like ECG or facial expressions, to provide a more holistic view of emotional states [58]. Additionally, future efforts could focus on refining the models to improve their cross-subject generalizability, possibly employing transfer learning or domain adaptation techniques to address variability among different individuals [2]. To facilitate real-time applications, there is also scope for designing lightweight model architectures that minimize computational demands while maintaining high accuracy [66]. Further, exploring alternative EEG datasets and electrode placements could contribute to the development of robust emotion detection systems with reduced hardware requirements, making them suitable for broader applications and wearable implementations [67].

IX. Conclusion

This study highlights the potential of using deep learning models—Bi-LSTM and GRU—to accurately classify emotional states from EEG signals, achieving high accuracy in both binary and multi-class classification tasks [37]. By applying preprocessing techniques and frequency-domain feature extraction, the models effectively identified patterns in EEG data linked to emotional responses [68]. The research underscores the feasibility of using EEG-based emotion detection for real-time applications, even with reduced electrode configurations, paving the way for practical, wearable systems that can monitor emotions in diverse settings [22]. The outcomes of this study support the development of emotion recognition applications across fields such as healthcare, where it could aid in early diagnosis and personalized treatment plans, and marketing, where it can enhance consumer engagement through emotionally adaptive content [29]. These findings establish a foundation for further exploration into the integration of EEG-based emotion detection with multimodal systems, advancing personalized, responsive technologies that adapt to human emotions in real time [30].

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