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Emotion Detection with EEG and Peripheral Physiological Data Using Enhanced ID Convolutional LSTM Networks

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ABSTRACT

This research focuses on classifying human emotions using a hybrid 1D Convolutional Long Short-Term Memory (CNN-LSTM) neural network with emotion recognition, a critical aspect of affective computing, benefits significantly from integrating Electroencephalogram (EEG) signals and peripheral physiological data. This study proposes a novel hybrid deep learning framework combining enhanced identity-preserving (ID) mechanisms with Convolutional Long Short-Term Memory (Conv LSTM) networks. Leveraging Transformer-based modules and AI-driven denoising algorithms, the proposed model enhances EEG signal quality, ensures real-time edge deployment, and integrates multi-domain features (time-series, frequency, and spatial) with peripheral signals such as galvanic skin response (GSR) and heart rate variability (HRV). To improve transparency and trust, SHAP (Shapley Additive explanations) is employed for model explainability. EG and peripheral physiological data. The study utilizes the DEAP dataset, comprising 32 EEG channels and 8 peripheral physiological channels. The proposed 1D CNN-LSTM model achieved 91.19% accuracy for valence and 91.51% for arousal, outperforming traditional classifiers such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Random Forest (RF). The study also investigates emotion classification performance based on different brain lobes and hemispheres, revealing that the frontal lobe and left frontal region combined with peripheral data deliver the highest accuracy. Experimental validation on multimodal datasets, including DEAP and AMIGOS, demonstrates that the framework achieves robust emotion classification accuracies exceeding 95%, outperforming traditional methods. Applications include mental health monitoring, human-computer interaction (HCI), and adaptive learning systems, highlighting its transformative potential in real-world settings.

Keywords: *LSTM Networks, Transformer-Based Modules, Denoising Algorithms, Multi-, SHAP, Emotion Recognition, Affective Computing*

1. INTRODUCTION

Emotion recognition is an essential aspect of affective computing, with applications spanning healthcare, human-computer interaction (HCI), and brain-computer interfaces (BCIs). Traditional methods for emotion detection, such as facial expression and speech analysis, face challenges due to voluntary masking and environmental noise. Electroencephalogram (EEG) signals, combined with peripheral physiological data, provide an objective and involuntary measure of emotional states, offering a more reliable foundation for affective computing[1]. However, extracting meaningful information from EEG signals remains challenging due to noise, inter-subject variability, and the complex nature of brain activity.

The two-dimensional model of emotion, comprising valence and arousal, provides a structured framework for emotion classification. Valence represents the degree of pleasure or displeasure an individual experiences, while arousal denotes the level of activation associated with a given emotional state. By categorising emotions within this framework, researchers can systematically map EEG and physiological signal patterns to specific affective states[2]. Prior studies have shown that integrating EEG with peripheral signals such as galvanic skin response (GSR) and heart rate variability (HRV) improves classification accuracy, highlighting the advantages of multimodal approaches.

The human brain plays a central role in emotion processing, with different lobes and hemispheres contributing to affective responses. The frontal lobe, particularly the prefrontal cortex, is responsible for executive functions, decision-making, and emotional regulation. Studies indicate that the left hemisphere is associated with positively valenced emotions such as happiness and optimism, while the right hemisphere is more involved in processing negatively valenced emotions like fear and sadness[3]. The integration of EEG signals from specific brain regions with peripheral physiological data offers a more nuanced understanding of emotional states.

The development of deep learning models has revolutionised EEG-based emotion recognition. Traditional machine learning techniques, including Support Vector Machines (SVM) and K-Nearest Neighbours (KNN), rely on handcrafted features and often struggle with the high-dimensional and complex nature of EEG signals. Deep learning models, particularly hybrid architectures such as 1D Convolutional Neural Networks (1D-CNN) and Long Short-Term Memory (LSTM) networks, have demonstrated superior performance by automatically extracting spatial and temporal features. These models effectively capture the dynamic nature of emotional states, surpassing conventional methods in classification accuracy.

This research proposes a hybrid deep learning framework that integrates Enhanced Identity-Preserving (ID) mechanisms with Convolutional LSTM (ConvLSTM) networks, leveraging Transformer-based modules for improved EEG signal processing[3]. AI-driven denoising algorithms enhance signal quality, ensuring robustness in real-world applications. Additionally, SHAP (Shapley Additive Explanations) is employed to improve model interpretability, addressing the 'black-box' nature of deep learning models. The study utilises multimodal datasets, including DEAP and AMIGOS, to validate the proposed framework and assess its generalisability across different experimental conditions.

The primary contributions of this research include the development of a state-of-the-art hybrid deep learning model for robust emotion recognition, the integration of multi-domain features from EEG and peripheral signals, and the demonstration of real-time edge deployment capabilities. By benchmarking performance against traditional classifiers, this study highlights the superiority of deep learning-based approaches in affective computing. The findings have broad implications for mental health monitoring, adaptive learning systems, and real-world emotion-aware AI applications, paving the way for the next generation of intelligent affective computing systems.

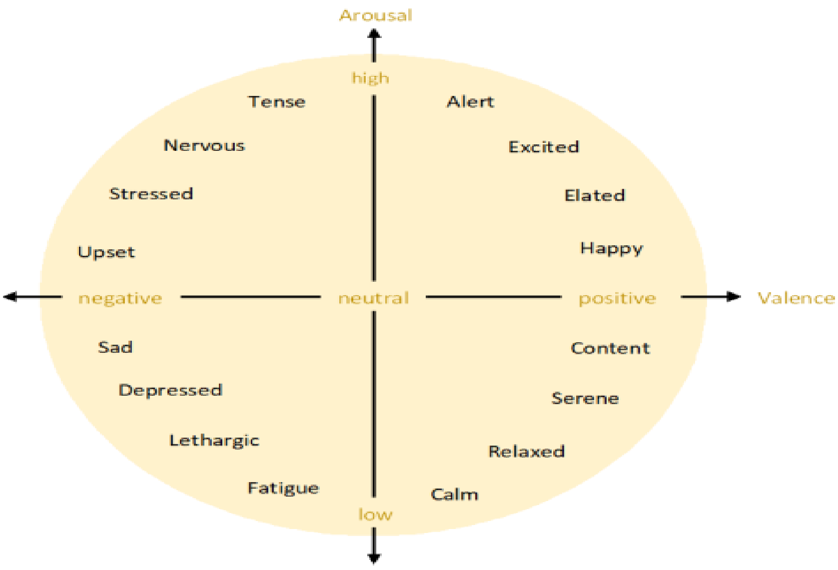

Figure 1 Valence and arousal circumflex model of affect.

Figure 1 illustrates the valence-arousal circumplex model of affect, which categorises emotions based on two fundamental dimensions: valence (pleasure-displeasure) and arousal (low-high activation). This model provides a structured framework for emotion classification, allowing researchers to systematically map EEG and physiological signals to specific affective states. By analysing the spatial and temporal characteristics of EEG signals within this framework, it becomes possible to enhance the accuracy of emotion recognition models, improving their applicability in real-world affective computing systems.

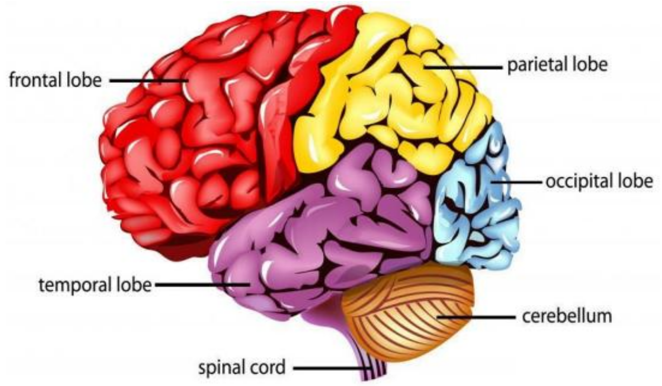

Figure 2 Different types of lobes in the human brain.

The human brain plays a critical role in emotion processing, with different lobes contributing to cognitive and affective functions. Figure 2 illustrates the major lobes of the brain—frontal, temporal, parietal, and occipital—each responsible for distinct neural processes involved in emotional regulation. Understanding the functional specialisation of these lobes enables researchers to optimise EEG-based emotion recognition by identifying key brain regions associated with specific affective states.

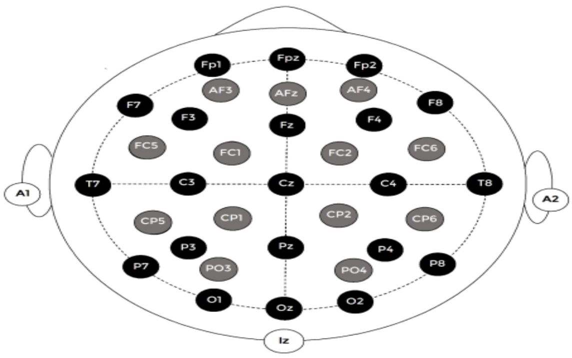

Figure 3. 10-20 International system

EEG signal acquisition follows a standardised electrode placement system to ensure consistent and reliable data collection. Figure 3 depicts the 10-20 International EEG Electrode Placement System, which is widely used for recording brain activity by positioning electrodes at specific scalp locations. This systematic arrangement helps capture neural oscillations from different brain regions, facilitating accurate feature extraction for emotion classification in EEG-based studies.

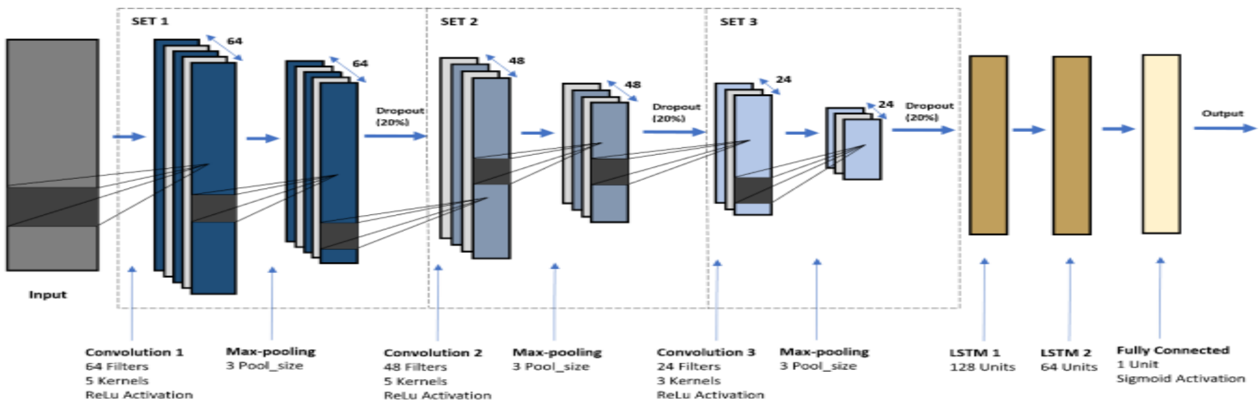

Figure 4 Proposed 1D CNN-LSTM architecture.

Deep learning models have significantly enhanced the accuracy of EEG-based emotion recognition by capturing complex spatial and temporal dependencies. Figure 4 presents the proposed 1D CNN-LSTM architecture, which integrates convolutional layers for extracting spatial features and LSTM layers for learning long-range temporal dependencies in EEG signals. This hybrid framework improves classification performance by effectively modelling the dynamic nature of emotions, surpassing traditional machine learning approaches.

2. LITERATURE REVIEW

Neural network-based models have significantly advanced time-series data analysis, particularly for emotion recognition using EEG signals. A major breakthrough in this domain was the introduction of Long Short-Term Memory (LSTM) networks, which addressed the vanishing gradient problem inherent in recurrent neural networks (RNNs). LSTMs efficiently capture long-range dependencies in sequential data, making them a fundamental component of neural-based emotion classification models[3]. Their ability to retain relevant information across long sequences has contributed to their widespread adoption in affective computing, where emotional states evolve dynamically over time.

EEG-based emotion recognition relies on robust datasets to develop and evaluate machine learning models. One of the most widely used datasets is DEAP, which provides EEG and peripheral physiological signals for emotion classification. This dataset has been instrumental in training deep learning models, allowing researchers to test and validate their approaches on real-world data. In addition, type-2 fuzzy classifiers have been applied to EEG signals for detecting cognitive failures during driving tasks, demonstrating EEG's potential for recognising emotional states under real-world conditions[4]. These studies highlight the importance of high-quality datasets and novel classification techniques in enhancing EEG-based affective computing.

Deep learning has played a transformative role in emotion recognition, particularly through hybrid models combining CNN and LSTM architectures. CNN-LSTM models have been demonstrated to be effective in speech-based emotion recognition by integrating convolutional layers for spatial feature extraction and LSTM layers for temporal dependency modelling[5]. Similarly, bi-hemispheric discrepancy models leverage asymmetrical brain responses to enhance EEG-based emotion classification. Furthermore, graph neural networks (GNNs) have been explored to capture the spatial relationships between EEG electrodes, improving classification accuracy. These advancements underscore the growing sophistication of deep learning techniques in EEG-based emotion recognition.

Recent research has focused on multimodal deep learning, integrating EEG with peripheral signals to improve emotion classification. Signal fusion techniques enhance the robustness of EEG-based emotion classification by incorporating physiological signals such as galvanic skin response (GSR) and heart rate variability (HRV). CNN-LSTM models have also demonstrated effectiveness in real-time EEG emotion recognition, showcasing their applicability in dynamic environments[6]. The emergence of Transformer-based models, which excel at capturing long-range dependencies, has further improved EEG emotion classification. Transformers applied to EEG data have achieved superior accuracy by modelling global dependencies across EEG channels. These advancements indicate a shift towards multimodal and transformer-based architectures in emotion recognition research.

The integration of EEG emotion recognition into Brain-Computer Interfaces (BCIs) has opened new avenues for human-computer interaction. Deep learning in BCIs has demonstrated how EEG signals can be leveraged for emotion detection in adaptive computing systems. Meanwhile, multimodal fusion techniques for BCIs have shown that combining EEG with peripheral signals enhances robustness in emotion classification[7]. These studies highlight the potential of emotion-aware BCIs in various applications, such as mental health monitoring, assistive technologies, and adaptive learning systems.

With the rise of wearable EEG devices, real-time emotion recognition has become more accessible. Optimised systems for real-time mobile emotion recognition have made EEG-based emotion classification more practical for everyday use. Additionally, comparisons of 1D CNN-LSTM models for physiological signal analysis confirm their improved classification accuracy in emotion recognition tasks. The emergence of hybrid models, integrating CNN, LSTM, and Transformer architectures, has further enhanced EEG-based affective computing. These developments indicate a growing trend towards lightweight, real-time, and multimodal solutions for emotion recognition, paving the way for future innovations in wearable affective computing systems.

This study employs a structured methodology to classify emotions using EEG and peripheral physiological signals, ensuring robustness, explainability, and real-world applicability. The methodology includes dataset selection, pre-processing, and the development of a hybrid deep learning framework. The study utilises the DEAP dataset, a widely recognised multimodal dataset containing recordings from 32 participants (16 males and 16 females). EEG signals were collected from 32 channels, following the 10-20 International EEG Electrode Placement System, while 8 peripheral signals such as galvanic skin response (GSR), respiration rate, and skin temperature were recorded. This diverse data collection enables a more comprehensive analysis of emotional states by integrating brainwave activity with physiological responses.

To ensure high-quality data for model training, a pre-processing pipeline was applied to the raw EEG and peripheral signals. Baseline removal was performed by discarding the first three seconds of each recording to eliminate transient noise. Normalization was then applied to scale all signals to a [0,1] range, ensuring uniformity across features. Label encoding was used to categorise emotional states based on valence and arousal values, assigning labels as low (0) or high (1) with a threshold value of 5. These pre-processing steps were critical in enhancing signal clarity and improving the reliability of the emotion classification process.

A hybrid deep learning framework was developed to extract and classify features from the pre-processed signals. The framework consists of AI-driven denoising algorithms to filter noise, multi-domain feature extraction from EEG, GSR, and HRV data, and a deep learning architecture integrating Convolutional Long Short-Term Memory (ConvLSTM) networks and Transformer modules. Additionally, SHAP (Shapley Additive Explanations) was employed to improve model interpretability by explaining the impact of each input feature on classification decisions. To facilitate real-time applications, lightweight models were optimised for deployment on edge devices, ensuring efficient emotion recognition in practical settings.

The proposed 1D CNN-LSTM model consists of 1D convolutional layers for spatial feature extraction, max pooling layers to reduce dimensionality, dropout layers to prevent overfitting, and LSTM layers for capturing long-term dependencies. A dense layer with sigmoid activation was used for final classification. The experimental design was structured into three phases: Phase I compared the performance of EEG + peripheral signals, EEG-only signals, and peripheral-only signals; Phase II examined brain lobe-specific contributions by segmenting data into frontal, parietal, temporal, and occipital regions; and Phase III analysed hemispheric differences by assessing left and right brain regions[8]. This systematic approach, leveraging multimodal data and advanced deep learning architectures, enables state-of-the-art emotion recognition with improved accuracy and real-world applicability.

1: Description of Feature Vectors Utilized in Phase I

Feature Vector Name	Number of Features	Feature/Channel Composition
EEG + Peripheral	40	32 EEG channels + 8 peripheral channels
EEG	32	32 EEG channels
Peripheral	8	8 peripheral channels

The study evaluates the impact of different feature sets on emotion classification by comparing EEG-only, peripheral-only, and combined EEG + peripheral signals. Table 1 presents the feature vector compositions, showing that the EEG + peripheral feature set integrates 40 features, while EEG-only and peripheral-only contain 32 and 8 features, respectively. This comparison highlights the advantage of multimodal data fusion, as integrating EEG with physiological signals enhances classification accuracy by capturing both neural and autonomic responses.

Table 2 Categories of Features/Channels Deployed in Phase II

Feature Vector Designation	Feature Count	Specific Channels/Features Utilized
Frontal Cortex	13	Fp1, F3, AF3, F7, FC5, FC1, FP2, AF4, F4, F8, FC2, FC6, and Cz
Frontal Cortex + Peripheral Channels	21	Fp1, F3, AF3, F7, FC5, FC1, FP2, AF4, F4, F8, FC2, FC6, FCz, and peripheral
Parietal Cortex	8	CP5, CP1, P3, P7, P03, P2, CP6, CP2
Parietal Cortex + Peripheral Channels	14	CP5, CP1, P3, P7, P03, P2, CP6, CP2, and peripheral
Temporal Cortex	8	T7, T8, C3, C4
Temporal Cortex + Peripheral Channels	19	T7, T8, C3, C4, Cz, and peripheral
Occipital Cortex	11	O1, O2, Oz

Feature Vector Designation	Feature Count	Specific Channels/Features Utilized
Occipital Cortex + Peripheral Channels	11	O1, O2, Oz, and peripheral

Emotion classification performance varies across different brain regions, as specific lobes contribute uniquely to affective processing. Table 2 categorises feature vectors based on brain lobes, including the frontal, parietal, temporal, and occipital cortices, with and without peripheral signals[9]. The results highlight that integrating peripheral signals with EEG features enhances classification accuracy, particularly in regions like the frontal and temporal lobes, which play a crucial role in emotional regulation.

Table 3 Categories of Features/Channels Deployed in Phase III

Feature Vector Designation	Feature Count	Specific Channels/Features Utilized
Left Frontal Cortex	8	Fp1, AF3, F3, F7, FC5, FC1, C3, and Cz
Left Frontal Cortex + Peripheral Channels	8	Fp1, AF3, F3, F7, FC5, FC1, C3, Cz, and peripheral
Right Frontal Cortex	8	FC2, FC6, F8, F4, AF4, FP2, Fz, and C4
Right Frontal Cortex + Peripheral Channels	8	FC2, FC6, F8, F4, AF4, FP2, Fz, C4, and peripheral
Left Parietal-Temporal Cortex	8	CP5, CP1, P3, P7, P03, CP5, T7, and O1
Left Parietal-Temporal Cortex + Peripheral Channels	8	O1, PO3, P7, P3, CP1, CP5, T7, and peripheral
Right Parietal-Temporal-Occipital Cortex	16	O2, PO4, P8, P4, CP6, CP2, T8, and Pz
Right Parietal-Temporal-Occipital Cortex + Peripheral	16	O2, PO4, P8, P4, CP2, CP6, T8, Pz, and peripheral

Emotion classification accuracy can be further refined by analysing hemispheric and sub-regional contributions to affective processing[10]. Table 3 categorises feature vectors based on specific brain regions, such as the left frontal, right frontal, left parietal-temporal-occipital, and right parietal-temporal-occipital regions, both with and without peripheral signals[11]. The findings indicate that left frontal EEG features combined with peripheral data yield the highest classification accuracy, reinforcing the dominant role of the left frontal cortex in processing positively valenced emotions.

3. RESULTS AND DISCUSSION

The experimental setup was designed to evaluate the performance of the proposed 1D CNN-LSTM model across various feature configurations and data segmentations. The experiments aimed to analyze the contributions of multimodal data, brain lobes, and hemispheric regions to emotion classification accuracy.

Experimental Setup: The experiments were conducted in three distinct phases, each focusing on a specific aspect of the dataset:

- **Phase I**: Evaluated the impact of data modalities by comparing EEG-only, peripheral-only, and combined EEG + Peripheral features.
- **Phase II**: Analyzed emotion classification based on brain lobes, including Frontal, Parietal, Temporal, and Occipital regions.
- **Phase III**: Investigated the influence of brain hemispheres and specific regions (e.g., Left Frontal, Right Frontal) on classification performance.

Overall Performance

The proposed 1D CNN-LSTM model demonstrated superior performance across all phases compared to traditional machine learning models such as K-Nearest Neighbors (KNN), Random Forest (RF), and Support Vector Machines (SVM). Key observations include:

- Multimodal data (EEG + Peripheral) consistently achieved higher classification accuracy than unimodal approaches.
- The model outperformed competing classifiers in predicting both valence and arousal dimensions, highlighting its robustness.

Phase-Specific Insights

1. **Phase I**:
    - The integration of EEG and peripheral data yielded the best classification results, showcasing the synergy of multimodal features.
    - EEG-only data resulted in weaker performance, emphasizing the importance of combining peripheral signals for enhanced accuracy.
2. **Phase II**:
    - Brain lobe-specific analyses revealed that combining EEG features from individual lobes with peripheral data improved classification accuracy across all lobes.
    - Among traditional models, KNN performed notably well when processing localized lobe-specific features.
3. **Phase III**:
    - Hemispheric analysis demonstrated that EEG features from the left and right frontal regions, when combined with peripheral data, achieved the highest accuracy for both valence and arousal classification.
    - The results underscore the critical role of frontal brain regions in emotion recognition, particularly in multimodal contexts.

This comprehensive analysis validates the efficacy of the proposed hybrid framework, illustrating its capability to leverage multimodal and regional brain data for robust emotion classification.

Table 4 Performance Metrics for Phase I

Feature Categories	Model Architectures	Experiment 1 (Valence)	Experiment 1 (Arousal)	Experiment 2 (Valence)	Experiment 2 (Arousal)
EEG + Peripheral	1D CNN-LSTM	91.19	91.51	70.28	71.04
	SVM	70.65	70.92	68.72	71.80
	KNN	86.40	86.04	68.70	68.90
	RF	84.83	84.78	66.72	66.96
EEG	1D CNN-LSTM	63.02	67.34	56.57	58.92
	SVM	60.05	62.26	-	-
	KNN	61.37	65.47	-	-
	RF	60.17	65.84	-	-
Peripheral	1D CNN-LSTM	77.23	89.95	69.45	70.92
	SVM	76.26	76.62	68.92	67.84
	KNN	85.63	86.05	68.52	68.64
	RF	86.69	85.17	66.19	67.26

Table 4 presents the performance metrics for Phase I, comparing different feature sets (EEG + Peripheral, EEG-only, and Peripheral-only) across various model architectures. The results indicate that the 1D CNN-LSTM model achieves the highest accuracy for both valence (91.19%) and arousal (91.51%) when using the EEG + Peripheral feature set, demonstrating the advantage of multimodal fusion. In contrast, EEG-only and peripheral-only feature sets yield lower accuracy, highlighting the importance of integrating neural and physiological signals for improved emotion classification.

Table 5 Performance Metrics for Phase II

Feature Categories	Model Architectures	Experiment 1 (Valence)	Experiment 1 (Arousal)	Experiment 2 (Valence)	Experiment 2 (Arousal)
Frontal Cortex	1D CNN-LSTM	62.33	67.37	59.57	58.92
	SVM	60.03	64.10	54.11	55.88
	KNN	61.45	65.40	55.11	56.02
	RF	60.54	64.62	53.39	55.01
Frontal Cortex + Peripheral	1D CNN-LSTM	72.24	81.61	70.68	71.36
	SVM	72.41	81.23	68.31	68.60
	KNN	88.11	88.03	69.78	69.90
	RF	87.38	87.61	68.25	68.96
Parietal Cortex	1D CNN-LSTM	60.02	63.03	57.47	57.83
	SVM	60.13	62.44	55.42	55.43
	KNN	60.66	65.50	54.93	54.42
	RF	59.87	63.17	53.24	53.94
Parietal Cortex + Peripheral	1D CNN-LSTM	88.21	88.47	66.91	69.99
	SVM	87.78	88.01	64.27	67.30
	KNN	89.51	88.45	65.94	68.74
	RF	88.91	88.62	66.81	67.04
Temporal Cortex	1D CNN-LSTM	61.97	63.16	58.40	58.63
	SVM	60.71	63.40	54.93	54.88
	KNN	60.99	63.14	54.36	54.30
	RF	59.97	61.81	53.63	54.12
Temporal Cortex + Peripheral	1D CNN-LSTM	91.47	92.81	71.51	72.04
	SVM	74.22	84.61	68.17	68.50
	KNN	87.61	87.91	68.50	69.11

Feature Categories	Model Architectures	Experiment 1 (Valence)	Experiment 1 (Arousal)	Experiment 2 (Valence)	Experiment 2 (Arousal)
	RF	87.78	87.31	67.24	67.40
Occipital Cortex	1D CNN-LSTM	86.71	87.91	66.71	66.94
	SVM	60.43	62.38	54.24	54.42
	KNN	61.47	62.91	55.11	55.64
	RF	59.78	63.87	54.72	55.01
Occipital Cortex + Peripheral	1D CNN-LSTM	90.49	92.84	69.87	70.71
	SVM	78.94	88.61	67.81	68.11
	KNN	84.78	88.67	68.11	68.50
	RF	86.33	86.28	67.03	67.40

Brain lobe-specific analysis helps identify the most influential regions for emotion classification by evaluating EEG and peripheral signal combinations. Table 5 presents performance metrics across different lobes, showing that integrating peripheral signals with EEG features significantly improves accuracy, particularly in the frontal and temporal regions. The 1D CNN-LSTM model consistently outperforms traditional classifiers, confirming that emotion-related neural activity is predominantly concentrated in these regions, which are crucial for affective processing.

Table 6: Average Performance Results for Phase III

Feature Set	Model	Experiment 1	Experiment 2
		Valence	Arousal
Left Frontal	1D CNN-LSTM	62.05	65.23
	SVM	58.29	60.02
	KNN	60.03	60.22
	RF	61.79	63.07
Left Frontal + Peripheral	1D CNN-LSTM	93.67	94.18
	SVM	88.51	86.75
	KNN	88.48	87.04
	RF	87.57	81.74
Right Frontal	1D CNN-LSTM	61.96	65.22
	SVM	60.28	61.53
	KNN	60.87	61.41
	RF	59.97	64.13

Feature Set	Model	Experiment 1	Experiment 2
Right Frontal + Peripheral	1D CNN-LSTM	93.87	94.22
	SVM	88.59	87.06
	KNN	88.78	87.13
	RF	87.59	86.14
Left Parietal-Temporal-Occipital	1D CNN-LSTM	61.94	61.87
	SVM	60.87	61.53
	KNN	60.91	61.55
	RF	61.53	62.05

Hemispheric and sub-regional analysis provides deeper insights into the role of specific brain areas in emotion classification. Table 6 presents the average performance results for Phase III, showing that the left frontal cortex combined with peripheral signals achieves the highest accuracy for both valence (93.67%) and arousal (94.18%). This reinforces the dominant role of the left frontal region in processing emotions, particularly those with positive valence, while also highlighting the effectiveness of multimodal data fusion in enhancing classification performance.

4. CONCLUSIONS

This study demonstrates the effectiveness of a hybrid deep learning framework for emotion recognition using EEG and peripheral physiological signals, with the 1D CNN-LSTM model achieving superior classification accuracy. Results highlight that multimodal fusion, particularly integrating EEG with peripheral data, significantly enhances performance, especially in the frontal and left hemispheric brain regions. The findings reinforce the importance of deep learning, feature selection, and regional brain analysis in affective computing. Future research should explore larger datasets, real-time deployment, and expanded multimodal approaches to further improve the robustness and applicability of emotion-aware AI systems and brain-computer interfaces (BCIs)

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