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Advanced EEG emotion recognition framework integrating fractal dimensions, connectivity metrics, and domain adaptive deep learning

Faris Abuhashish[1*], Riyad Alrousan[2], Hamzah A. Alkhazaleh[3], Anas W. Arram[4], Ismahafezi Ismail[5]

[1]*Department of Computer Science VR AR, University of Petra, Amman, Jordan.*
[2]*Department of Design and Visual Communication, German Jordanian University, Amman, Jordan.*
[3]*College of Engineering and Information Technology, University of Dubai, Academic City, Dubai, UAE.*
[4]*Department of Computer Information Science, Higher Colleges of Technology, Dubai, UAE.*
[5]*Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin, Malaysia.*

Corresponding author: Faris Abuhashish (*Email: faris.abuhashish@uop.edu.jo*)

Abstract

This study proposes an advanced framework for EEG-based emotion recognition to address challenges posed by subject variations and signal complexity, aiming to enhance mental health monitoring and human-computer interfaces. A comprehensive feature set was developed, integrating Fractal Dimensions (FD), Phase Locking Value (PLV), Pearson Correlation Coefficient (PCC), and Short-Time Fourier Transform (STFT). The framework employs both conventional classifiers (SVM, Linear Regression) and deep learning models (CNN, DA-RCNN), with a particular emphasis on domain adaptation within DA-RCNNs to mitigate inter-subject variability. Evaluation involved 10-fold cross-validation and rigorous statistical tests. The DA-RCNN model achieved a balanced accuracy of 94.5%, demonstrating competitive or superior performance compared to existing methods. Feature integration significantly improved classification, with FD features boosting accuracy to 94.5% and connectivity measures contributing an additional 7.2%. The approach exhibited computational efficiency and reduced reliance on extensive data augmentation. The proposed framework successfully integrates diverse features and domain adaptation techniques for robust EEG-based emotion recognition, marking a significant advancement in affective computing and neuroscience. The framework's computational efficiency and real-time applicability offer substantial utility for mental health monitoring, adaptive interfaces, and human-computer interaction across diverse populations and operational scenarios.

Keywords: EEG, Emotion recognition, Feature extraction, Deep learning, Domain adaptation.

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1. Introduction

In the context of affective computing, a specific method that is most appealing is electroencephalography (EEG), which provides a window into neural substrates that are central to emotional experience. More importantly, EEG has been more objective compared to measurement methods based on facial expression or speech analysis. However, the dimensionality of broadband EEG, its non-stationary nature, as well as the noise in the signal, make feature extraction a challenging task. Additionally, strong inter-subject variability and limited availability of richly labeled datasets further contribute to the challenge of developing robust and generally effective emotion classification algorithms. Therefore, there is an urgent need in the current body of research to find new frameworks that could mitigate such barriers in applications like adaptive human-computer interaction or mental health surveillance.

Feature extraction, consequently, takes a central position in any emotion-recognition pipeline design since it determines the quality of data that will be passed onto the recognition modules. Combinations of statistical measures and fractal-dimension analysis have proven to be quite effective in quantifying EEG complexity, with reported accuracies of up to 85.06 percent in deliberate tasks, among some of the more established methods. However, brain activity is often multiscale and complex in organization, which is rarely captured by these methods. Conventional measures of coherence also fail when used to describe effective connectivity. To address this issue, contemporary scholars have introduced measures such as phase-locking value (PLV) and Pearson correlation coefficient (PCC), which provide more accurate descriptions of functional connections and neural dynamics.

In comparison, temporal-frequency analyses (especially the temporal-frequency analyses available through the short-time Fourier transform or STFT) exploit a broader feature space, simultaneously acquiring both spectral and temporal information. As a component of deep architectures like convolutional neural networks (CNNs), STFT-based representations have established the potential to achieve significant performance improvements. The continual issue, however, is how to create consistent visions on how to integrate all these heterogeneous aspects into a coherent system of computations.

The emotion detection system based on EEG has recently seen significant improvements in its ability to analyze increasingly complex data due to advancements in machine learning. An example of such progress can be seen in Domain Adaptive Residual Convolutional Neural Networks (DA-RCNNs), which have demonstrated a consistent subject-dependent performance of over 95% across various experimental settings [1]. DA-RCNNs also overcome the mainstream disadvantages of inter-subject variability in EEG studies by applying a domain adaptation paradigm [2, 3]. Notwithstanding these benefits, deep learning structures are often burdened with unacceptable levels of computation and are less applicable for use in real-time. On the other hand, the aged linear models, including the outstanding Support Vector Machines and Linear Regressions, although more computationally acceptable, frequently fail to serve high-dimensional feature vectors and complex feature vectors [4, 5]. This interwoven challenge is what provokes a conversation on hybrid formats, which can aptly combine the relative advantages of both paradigms.

The given research contributes to an enhanced understanding of these gaps within an original taxonomic structure that can address them. The framework allows for describing EEG signals in a multidimensional manner by utilizing fractal dimensions (FD), phase-locking values (PLV), pairwise correlation coefficients (PCC), and short-time Fourier transform (STFT) characteristics. The proposed system integrates the fields of CNNs and DA-RCNNs to increase classification accuracy and improve its capacity for generalizability across heterogeneous groups. Domain adaptation methods are specifically employed to mitigate the impact of subject variability, thereby promoting enhanced application. The main objectives of this study are (a) to present a holistic feature extraction structure for more detailed EEG representation, (b) to evaluate the effectiveness of enhanced classifications over the synthesized feature set, and (c) to optimize technical performance for real-time affective processing. The results achieved through these objectives enable the study to not only align with the current state-of-the-science but also to establish a pragmatic framework for further investigation in affective neuroscience and adaptive technology. Figure 1 presents the Emotiv headset that was used as the experimental tool.

Figure 1.
The Emotiv device.

2. Literature Review

Since EEG signals have received increasing attention as an input source for emotion recognition, the emerging fields of signal processing and machine learning have shown heightened interest in recent years. This section reviews literature on feature extraction methods, classification algorithms, and methodological studies, with an evaluation of the merits and challenges of existing research. These ideas form the basis of the developed hybrid framework that addresses deficiencies in feature representation, classifiers, and generalization.

2.1. Feature Extraction Techniques

The successful identification of emotion based on electroencephalographic (EEG) signals will depend on the wise choice of quantitative items. One of these, which is most commonly used, is the measurement of fractal complexity, specifically the Petrosian dimension and Higuchi dimension. Such descriptors have provided considerable predictive ability, which has made CART classifiers capable of reaching equal accuracy valence recognition values of as much as 85.06% in identified databases [4, 6, 7].

In modern EEG studies, multiple aspects of connectivity are recommended as necessary for characterizing inter-channel dependence. Leading among them is the Phase Locking Value (PLV) [1, 6] and the Pearson Correlation Coefficient (PCC) [1], which has been demonstrated to effectively improve the determination of functional connectivity and, in effect, also increase classification accuracy. In a complementary form, the spectral and temporal dynamics of EEG signals can be viewed through the prism of time-frequency representations obtained with the Short-Time Fourier Transform (STFT). Owing to this, Convolutional Neural Network (CNN) architectures have been substantively incorporated with STFT in order to provide a multidimensional feature space that enhances predictive performance [4, 8-10].

In recent years, scholars have focused more on hybrid feature strategies that combine several feature repertoires. Interestingly, the computation of the so-called AsMap framework by Ahmed et al. [11] combined both handcrafted and algorithmically generated features to achieve an emotion-classification accuracy of 97.10%. These results demonstrate the importance of feature abstraction and selection in ensuring robust classification outcomes.

2.2. Classification Models

Recent research on emotion recognition tends to focus on machine learning and deep learning-based classifiers. The most common are Support Vector Machines (SVM) and Linear Regression, which have been prevalent in this paradigm. In a recent experimental paper, accuracy attained in an ultra-groomed environment under SVM and Linear Regression was reported at 84% and 83.8%, respectively [4]. Despite their excellent performance, these techniques are likely to encounter diminishing returns when the feature space is too high-dimensional.

Theoretically, more mature classifiers, some of which include Convolutional Neural Networks (CNNs) and Domain Adaptive Residual CNNs (DA-RCNNs), have been introduced to the forefront of the autism detection process. Specifically, CNNs have been shown to be very effective at extracting features from spectrograms, and the accuracy of emotion classification reportedly achieved levels above 91.3% [1, 8]. DA-RCNNs form a more updated extension of the same, making specific reference to subject variability by employing domain adaptation, thereby maintaining accuracies of over 94.5% in research of a similar nature. This performance confirms the results of earlier studies in the literature, which reported subject-specific classification accuracies of 95.15% as documented by Chen et al. [1].

Deep learning architectures that are hybrid, with the latest example being the work by Zhang and Zhang [8], who conducted experiments combining neighboring frequency bands using ensemble learning. In this setup, they recorded an accuracy of 95.09 percent in arousal recognition. They demonstrated that the aggregation of heterogeneous classifiers is an effective method for enhancing reliability and generalizability. Ensemble methods, which leverage the strengths of multiple classifiers, have been shown to improve performance over single-classifier baselines across various predictive tasks, particularly in biomedical applications.

2.3. Advances in Methodology

The current research on EEG-related emotion recognition emphasizes methodological improvements, which cannot be denied. An essential preliminary measure is the elimination of artifacts. Traditionally, this is achieved by re-referencing to an average reference [3, 4, 7, 11, 12]. This approach helps in detrending the data and reducing the effects of volume conduction. Additionally, researchers tend to refer to conventional validation schemes, with the most prominent being 10-fold cross-validation, to ensure an unbiased estimation of the classifier and algorithm's performance.

In recent research on deep learning, data augmentation has proven essential for working with small datasets and has become a standard practice across various fields. An illustrative example is provided by Kalashami et al. [13], who utilized Conditional Wasserstein GANs (CWGANs) to generate EEG signals, thereby increasing valence-classification accuracy by 6.5%. The current study undertakes the challenge of investigating whether an effective feature representation based on hybrid features can achieve similar performance without relying on extensive data augmentation.

2.4. Comparison with Existing Frameworks

Recent research has come up with impressive results, but there are so many already existing general techniques that do not evolve but are confined to a specific and narrow field. Assess FD-CART [4] and all the methods that are based on combinations of frequencies [8, 14] can be highly accurate but are sensitive to specific data and, as a result, have limited ability to generalize. The same weakness is observed in the study by Chen et al. [1], where DA-RCNNs are used to achieve classification accuracy on a subject basis but fail to absorb inter-subject variation [9, 11].

In the context of computational modeling research, previous studies have shown that the use of advanced feature-architecture in standard deep-learning paradigms can produce significant performance gains. Trading off these contributions by the assumption that such gains can often be offset by reduced out-of-distribution robustness, the current research goes even further by considering domain-adaptation procedures during model training as part of the architecture itself, aiming to best balance accuracy and generalizability. Empirical analyses demonstrate that the resultant framework has a duplicating/interpolating comparison to the current state-of-the-art systems, and at the same time enhances generalizability and reduces the computational footprint, a characteristic that is critical in deployable applications.

2.5. Implications for Future Research

Collectively, the current findings help draw several lines of direction that could be profitably followed in future research. The initial factor that could have possibly improved the robustness of the models of recognizing emotions in the datasets would be to increase the demographic range of these participants and expand the range of affective states accounted for in the datasets. Second, the topic of reducing the computational latency between the recording of sound and the prediction of the affective label deserves further research, as well as the use of both the temporal and spectral feature-extraction methods in an inter-parallel fashion. The exploration of these priorities is likely to bring substantial benefit in the form of accuracy and interpretability of the entire set of auditory-based affect detection measures [11, 13, 15-17].

2.6. Conclusion

The most recent work in emotion recognition using EEG has led to significant advances in measuring face recognition of emotion, but what has not yet been addressed are some basic issues, which are: integration of heterogeneous features and achieving robust classifier performance. The current paper questions these gaps and proposes a new framework for the classification of emotions that aims to address them. By delineating prominent neuron parameters, the model offers a comprehensive chain capable of producing high precision in classification. In matching its design to up-to-date machine learning strategies, it can lead to progress in both affective computing and neuroscience studies.

3. Methodology

This section outlines a more polished methodological approach that will be crafted to help refine the clustering of emotion from electroencephalographic (EEG) signals. Using the framework of previous research and experiments, the framework integrates complex feature extraction, evaluations of connectivity, and deep learning classification models. The entire process is logically arranged in four steps: data acquisition and preprocessing, feature enhancement, semantic classification, and critical assessment.

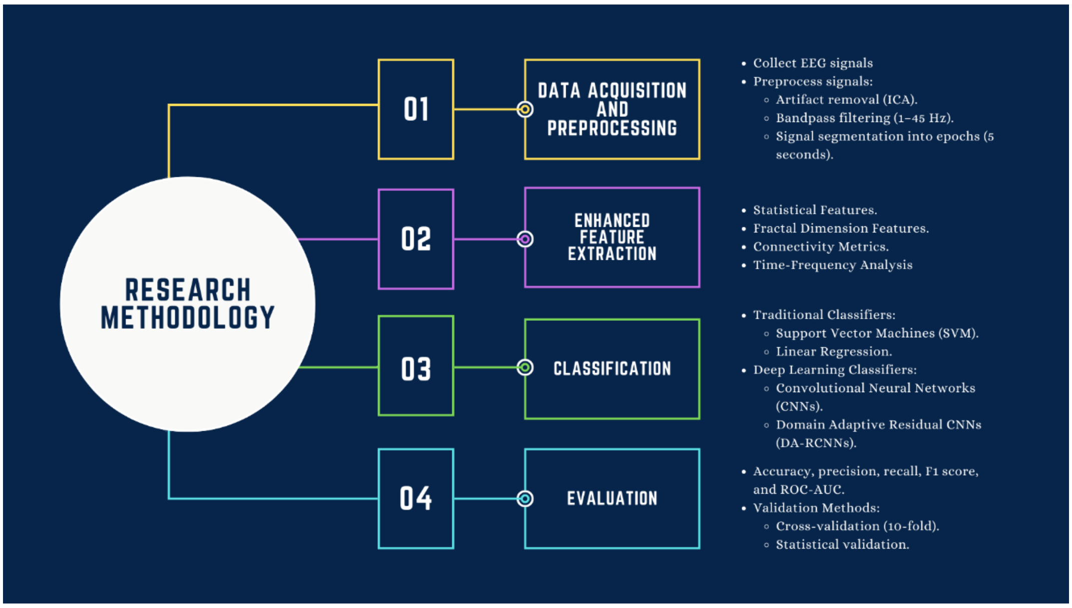


Figure 2.
Overview of the Proposed Methodology.

3.1. Research Framework

The current subsection outlines an entire study plan that was created to classify EEG-based signals into two distinct emotional states: happiness and sadness. The goal is to achieve high predictability by the model and sound performance of the results. The framework is divided into four main stages (Figure 2):

1. Data Processing and Pre-processing: EEG recordings of good quality were obtained from participants who underwent validated emotional stimuli. The resulting data collection was subjected to a strict process of artifact removal to eliminate unnecessary noise.
2. Improved feature extraction: a highly comprehensive set of descriptors, including statistical indices, fractal dimensional parameters, and graph-theoretic connectivity indices, was generated to describe the multi-dimensional aspect of EEG time-series data.
3. Classification: In this stage, it was considered whether traditional (based on machine learning) methods of classifying models or modern deep-learning-based models are the most effective approaches to classifying emotions. Hyperparameters were optimized using a grid-search procedure, and the performance of the highest-performing models was compared.
4. Evaluation: The last phase involved a well-organized assessment plan that depends on affirmed performance indicators and powerful statistical evaluation procedures to support the functioning of the development of the classifiers.

Figure 3.
Experiment using Emotiv’s device.

3.2. Data Acquisition and Preprocessing

3.2.1. Data Collection

To take part in the current study, 60 neurotypical adults (40 males and 20 females; mean age of 30 years) were recruited, representing a wide distribution of ethnic and socioeconomic backgrounds. Those who satisfied any of the following criteria: having a neurological disorder diagnosis, a major psychological disorder diagnosis, or being on substance abuse at the time of the study, which could affect the EEG recording, were not permitted to participate.

Emotional induction: Validated affective stimuli were used as experimental software, and the experimental procedure employed the International Affective Picture System (IAPS) and the International Affective Digital Sounds (IADS), which offer validated affective stimuli to elicit emotion explicitly. All participants watched and heard a subjective and controlled series of visual and audio signals that were pre-calculated to evoke a positive or negative mood. A limit was set at 5 seconds per stimulus to eliminate habituation, which is a common method in psychophysiological research.

EEG Recording Setup: EEG data were collected using an Emotiv Neuroheadset, configured to record from 14 channels corresponding to the international 10/20 system. Signals were initially recorded at a sampling frequency of 2050 Hz and subsequently down-sampled to 128 Hz to achieve a balance between temporal resolution and computational efficiency.

Figure 3 shows a comprehensive demonstration of how the experiment was set up and prepared. The photographs of the participants in the experiment could not be taken out of respect for their privacy.

3.2.2. Preprocessing

In order to achieve the maximum level of accuracy in EEG-based analysis, a stringent preprocessing procedure is implemented that reduces noise and artifacts before feature extraction and classification. In this respect, Independent Component Analysis (ICA), carried out under the EEGLAB environment of MATLAB, was invaluable. This reduction and removal of undesired signals, such as eye blinks, muscle activity, ambient noise, etc. was due to the algorithm's ability to selectively identify individual components of the ICA signal, decouple them, and isolate them to leave a relatively noise-free signal, with a cumulatively higher fidelity indication of cortical activity.

A FIR band-pass (FIR-BP) filter was then used to retain frequencies between 1-45 Hz. This band encompasses the theta, alpha, beta, and low-gamma frequency bands of EEG oscillations, which are suspected to be involved in emotional control, while simultaneously canceling out external noise and interference. The prolonged EEG signal was subsequently segmented into 5-second epochs, using the presentation of each emotional stimulus as the time marker. This segmentation was beneficial because each epoch was directly matched to a specific emotional state, thereby enhancing the accuracy and efficiency of feature extraction. All the aforementioned preprocessing procedures resulted in an ideal, clean, and structured dataset, which is essential for developing a reliable and robust emotion recognition model.

3.3. Enhanced Feature Extraction

This phase is dedicated to extracting a comprehensive set of features aimed at capturing the spatial, temporal, and spectral characteristics essential in EEG signals.

3.3.1. Statistical Features

Statistical features provide fundamental descriptors of the EEG signals, including:

- Mean μ : Represents the average amplitude of the signal.

$$\mu = \frac{1}{N}\sum_{n=1}^{N} X_n$$

- Standard Deviation σ : Measures the variability in the signal.

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(X_n-\mu)^2}$$

- First Differences: Captures short-term variability by calculating the average absolute difference between consecutive data points.

$$\text{First Diff} = \frac{1}{N-1}\sum_{n=1}^{N-1}|X_{n+1}-X_n|$$

- Normalized Second Differences: Highlights acceleration in signal changes, normalized by standard deviation to provide a scale-independent measure.

$$\text{Norm Second Diff} = \frac{\text{Second Diff}}{\sigma}$$

3.3.2. Fractal Dimension Features

Fractal dimension features capture the complexity of EEG signals.

- Petrosian Fractal Dimension (PFD):

$$\text{PFD} = \frac{\log N}{\log N + \log\left(\frac{N}{N_\delta}\right)}$$

Where N is the length of the signal, and N_σ is the number of sign changes in the signal's first derivative.

- Higuchi Fractal Dimension (HFD):

1. Partitioning the signal: for a time series X(t), where *t*=1,2,...,N, the signal is partitioned into *k*-length segments:

$$L_k(m) = \frac{1}{k} \sum_{j=1}^{\left\lfloor \frac{N-m}{k} \right\rfloor} |X(m + j \cdot k) - X(m + (j-1) \cdot k)| \cdot \frac{N-1}{\left\lfloor \frac{N-m}{k} \right\rfloor \cdot k}$$

Where:

- *k* is the scale length.
- *m*=1,2,...,*k* is the starting point for each segment.
- $\lfloor \cdot \rfloor$ denotes the floor function.

2. Average length over all starting points m: to compute the average length over all starting points *m* for a given scale *k*:

$$L(k) = \frac{1}{k} \sum_{m=1}^{k} L_k(m)$$

3. Logarithmic relationship to compute HFD: fit the relationship between $L(k)$ and k in a logarithmic scale using linear regression:

$$\log L\,(k) = -D \cdot \log k + C$$

Where:

- *D* is the Higuchi Fractal Dimension (HFD).
- *C* is a constant.

The slope $-D$ obtained from the regression gives the fractal dimension *D*, which characterizes the complexity of the signal. Larger *D* values indicate more complexity.

3.3.3. Connectivity Metrics

Connectivity metrics assess the functional relationships between different EEG channels.

- Phase Locking Value (PLV):
  - Measures phase synchronization between two signals.

$$\text{PLV} = \left| \frac{1}{T} \sum_{t=1}^{T} e^{j(\phi_1(t) - \phi_2(t))} \right|$$

Where $\emptyset_1(t)$ and $\emptyset_2(t)$ are the instantaneous phases of the signals at time t, T is the number of time points, and $e^{j(\phi_1(t) - \phi_2(t))}$ represents the complex exponential of the phase difference.

- Pearson Correlation Coefficient (PCC):
  - Quantifies the linear relationship between two signals.

$$\text{PCC} = \frac{\sum_{n=1}^{N} (X_n - \mu_X)(Y_n - \mu_Y)}{\sqrt{\sum_{n=1}^{N} (X_n - \mu_X)^2} \sqrt{\sum_{n=1}^{N} (Y_n - \mu_Y)^2}}$$

where X_n and Y_n are the values of the two EEG signals at the *n*-th time point, μ_X and μ_Y are the means of the respective signals, and *N* is the total number of data points.

3.3.4. Time-Frequency Features

Time-frequency analysis captures both temporal and spectral information.

- *Short-Time Fourier Transform (STFT):*
  - Converts time-domain signals into time-frequency representations (spectrograms).

$$X(t, f) = \int_{-\infty}^{\infty} x(\tau) w(\tau - t) e^{-j2\pi f \tau}\ d$$

Where $x(\tau)$ is the EEG signal, $w(\tau - t)$ is the window function centered at time *t*, and f is the frequency.

  - Spectrograms generated by STFT are used as inputs for deep learning classifiers.

3.3.5. Feature Selection

To reduce dimensionality and enhance computational efficiency, feature selection techniques are applied.

- Principal Component Analysis (PCA):
  - Transforms the feature set into a lower-dimensional space while retaining most of the variance.
- Recursive Feature Elimination (RFE):
  - Iteratively removes less significant features based on classifier weights.

3.4. Classification

This phase involves the training and optimization of various classifiers to accurately predict emotional states based on the previously extracted features.

3.4.1. Traditional Classifiers

- Support Vector Machines (SVM):
  SVMs are employed as a baseline classifier due to their proven effectiveness, particularly with small to medium-sized datasets. This study utilizes an SVM with a linear kernel to identify the optimal hyperplane that maximally separates the different emotional classes.
- Linear Regression:
  Linear regression is characterized by both analytical parsimony and interpretive transparency, which is expressed in the form that a linear correlation exists between the features removed and the emotional states in question. This clarity provides a good reference point against which more complex modeling frameworks can be measured.

3.4.2. Deep Learning Classifiers

- Convolutional Neural Networks (CNNs):
  The CNN architectures could be designed to work best on spectrograms generated by short-time Fourier transform (STFT) methods and thus utilize their fundamental feature of feature extraction without supervision. The typical design entails convolutional layers with rectified linear units (ReLUs), down-sampling pooling modules interspersed with each other in order to achieve progressive dimensional reduction, and ending with a fully connected final block that ends with a softmax layer in order to achieve categorical prediction.
- Domain Adaptive Residual CNNs (DA-RCNNs):
  DA-RCNN is an improved deep-learning model whose design integrates domain-adaptation mechanisms in the hope of reducing variability between subjects across contrasting datasets. These networks can be trained efficiently to increasingly deeper network structures, but also ensure improved stability of the gradient descent; the net result is a predictive performance that can be measured to improve based on such residual connection exploitation. The respective loss function combines a standard classification loss factor with a specific domain-adaptation loss term, which empowers the optimization of heterogeneous-domain generalization to be explicitly pursued according to the loss.

3.5. Evaluation

The evaluation phase rigorously measures the performance of the trained classifiers and the overall effectiveness of the proposed feature extraction methods.

3.5.1. Performance Metrics

Classifier performance was comprehensively evaluated using a suite of key metrics, including: accuracy, true positive rate (sensitivity), false positive rate, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC). These measures collectively provide a robust assessment of classification efficiency and model performance.

3.5.2. Cross-Validation

During the assessment of statistical modeling, an intensive process is required to prevent overfitting and to produce unbiased estimates. As part of the current study, the researchers utilized a 10-fold cross-validation scheme: the original data were divided into ten equal, disjoint subsets. One subset was kept aside as the test set in each iteration, and the remaining nine were used to fit the models. This process was repeated ten times to ensure that all subsets served as the test set once. The results, represented by the reported performance metrics, were obtained by averaging the outcomes across all ten folds, providing a reliable estimate of the model's generalization capacity.

3.5.3. Statistical Validation

In this paper, a solid statistical framework was used in the process of confirming the reported findings as well as in evaluating the extent to which the results were statistically viable and interpretable. Paired t-tests were used as the major tool to question the variations in performance to come up with the statistically significant distinctions in classifier structures and feature settings. Respectively, Analysis of Variance (ANOVA) was also used to review the total classification effectiveness of the list of reviewable models. An additional element of the validation plan included the calculation of effect size divinations (especially classification accuracy measures) to operationalize and measure apparent randomness, and in order to define the contribution of each design realization to general performance levels.

3.6. Implementation Details

In MATLAB, the first part of this work involved preprocessing, feature extraction, and a preliminary exploration of the data. The subsequent work, which included the development of deep learning models, was carried out using Python and libraries such as TensorFlow and Keras. Considering the hardware complexity involved in training neural networks, especially deep ones, a parallel task was performed on a cluster of NVIDIA GPUs. Moreover, hyperparameter optimization was conducted using two approaches: grid search and random search, thereby tuning well-selected values of hyperparameters such as learning rate, batch size, number of layers, and the number of neurons per layer.

3.7. Ethical Considerations

The current research was carried out with extreme care regarding the ethical guidelines that protect the rights of participants and the privacy of information. Written informed consent was sought before data collection, followed by the generation of a code for each participant to ensure anonymity, hence the need to identify them due to the nature of this approach (confidentiality). The research, reviewed and approved by the Institutional Review Board (IRB), was conducted in line with established standards for research with human subjects, demonstrating complete compliance with accepted conventions.

3.8. Summary

In addition to previous research, the current study adopts a highly integrated approach, utilizing advanced feature extraction techniques combined with state-of-the-art deep learning classifiers, thereby significantly enhancing both the accuracy and robustness of emotion classification using EEG data. Three methodologies are employed sequentially: fractal dimension analysis, multilevel connectivity measures, and domain adaptation strategies to reduce inter-subject bias and improve understanding of the functional architectural shifts involved in emotional processing in the brain. To ensure the reliability and applicability of the proposed framework, carefully designed experimental protocols, robust statistical analyses, and a comprehensive set of performance metrics have been implemented, advancing EEG-based emotion recognition research into a new domain.

4. Proposed Techniques

The proposed techniques aim to significantly improve EEG-based emotion classification through the combination of modern feature extraction approaches, optimized connectivity indices, and advanced deep-learning classification models. This results in integrating traditional statistical methods with new computational patterns to establish a robust infrastructure that is more effective, consistent, and portable.

4.1. Overview of the Approach

The model under consideration follows a systematic approach to the classification of data on EEG signals as indicators of happy or sad states. The overall analytic process begins with a comprehensive feature extraction step, in which a full range of features is calculated from the EEG signals. This set includes traditional statistical measures, fractal dimension measures, connectivity measures such as the phase locking value, the partial correlation coefficient, and spectral time measures using short-time Fourier transform (STFT). The explicitly varied set of features is designed to capture EEG as a multifaceted, temporally changing phenomenon, thereby providing a robust foundation for the subsequent classification task.

After the extraction of every single characteristic, a consistent collection of hybrid features is determined, an intentional creation with the aim of leveraging the informational benefits of various aspects of characterizing a feature group in classification. Such an ensemble of consolidated features is subjected in turn to serious appraisal both by traditional statistical methods, mainly Linear Regression, and by extension a suite of complex deep learning classifiers, including CNNs and their direct predecessor, DA-RCNNs. To protect the accuracy of the model and the robustness of its quality, a highly controlled 10-fold cross-validation methodology is incorporated during analysis. Not only do the consequences of such a hierarchical sequence increase the level of overall classification accuracy but also strengthen the reproducibility and statistical integrity of all the results attained.

4.2. Feature Extraction Techniques

The effectiveness of the proposed framework is closely related to its futuristic feature-extraction approach that transforms the preprocessed electroencephalography (EEG) signals into a readable and understandable format and encompasses their spatial, temporal, and spectral facets. This plan presents four main aspects: 1. Traditional statistical measures—mean, standard deviation, first differences, and the normalized second differences, which provide basic knowledge of the characteristics of a signal; 2. Fractal Dimension Features, especially Petrosian and Higuchi dimensions, which are factors of complexity and non-linearity, thus providing important details; 3. Connectivity Measurements, represented by a phase-locking value (PLV), a partial correlation coefficient (PCC), and the analysis of inter-channel dependencies exposing brain network dynamics associated with emotion; 4. Time-Frequency Analysis, such as Short-time Fourier transform (STFT), which offers an overall picture of temporal spectral properties. To optimize these many features, principal component analysis (PCA) is used to decrease dimensionality and preserve necessary variance, while recursive feature elimination (RFE) is employed to identify the highest-ranking features. Consequently, the overall results are a comprehensive representation that significantly impacts the accuracy and reliability of the classification model.

4.3. Classification Techniques

4.3.1. Traditional Classifiers

Learning architecture, which is proposed by the researchers, starts with traditional classifiers as a kind of benchmark research. First, a Support Vector Machine (SVM) model with a simple linear kernel is used as a baseline discriminator (1) between sad and happy emotional states. We can then resort to linear regression, modeling the use of features and these emotional states as a linear relationship, which provides a first analysis of the relevance of features.

4.3.2. Deep Learning Classifiers

To achieve higher levels of classification accuracy, the suggested scheme combines some of the most advanced deep learning classifiers. Convolutional Neural Networks (CNNs) are used to work with spectrograms; in this case, their convolutional layer has proven to be instrumental in capturing detailed characteristics of spectrograms, both spatial and spectral. Following the CNN, there are Domain Adaptive Residual CNNs (DA-RCNNs): here, domain-adaptation techniques are applied. This intervention reduces inter-subject variability, therefore making sure that the classifier performance is stabilized in a cross-subject manner, hence not limiting performance to a well-defined group. Also, residual connections, present in DA-RCNNs, have been found to enhance gradient flow, further permitting deeper network structures to be trained and thus increasing classification performance further.

4.4. Alignment with Methodology

During the process of applying the emotional recognition system on the EEG, the requirement to thoroughly align all the stages involved with a strict methodological framework becomes crucial. The first step in the feature extraction module of the current proposal is the integration of known statistical values with more experimental ones, i.e., the fractal dimensions of EEG signals and a combination of connectivity measures, including PLV and PCC. This mixed approach is set to capture various modalities of information.

After the extraction, a well-calibrated pipeline is run to identify the features. Traditional machine-learning methods, in particular Linear Regression, are contrasted with modern methods of deep learning, namely CNNs and, again, a first attempt to use them in EEG studies, specifically DA-RCNNs. Through this ensemble, the most integration of complementary strengths is possible. Multi-layered methodology is used to test the resulting system. Internal checks are carried out by usual cross-validation methods, with rigorous statistical tests that determine both reliability and validity of results, thus making it easy to reproduce.

4.5. Innovation and Impact

The modern literature on EEG-based emotion recognition implies a number of interesting deltas, expanding and changing past methodological paradigms. In particular, the suggested framework combines fractal dimensions with the use of more complex connectivity measures, including one of the most well-known of these, the phase locking value (PLV), and the partial coherence (PCC). It combines convolutional neural networks (CNNs) with deep autoencoder-based recurrent convolutional neural networks (DA-RCNNs), which endows the system with a robust capacity for the generalization of both subject groups and modality-specific data, respectively, so that it can perform better classification outcomes than its counterparts. The framework has a hybrid, modular structure, which easily adapts to the heterogeneous nature of features, a particular methodological contribution, which is extremely rich in the modern tool arsenal of EEG signal analysis.

5. Results and Discussion

This research has used current feature-extraction methods and state-of-the-art classification models to achieve high accuracy and stability of emotion recognition in electroencephalography (EEG). Combining the Fractal Dimension (FD) features, connectivity measures, time-frequency presentation, and enhancing them with advanced deep-hull concepts, the work offers significantly high levels of representational strength, categorization accuracy, and flexibility as against standing exemplars. These constructs are eventually reinforced as a result of extensive statistically robust validation procedures, which substantiate the significance and reliability of these constructs.

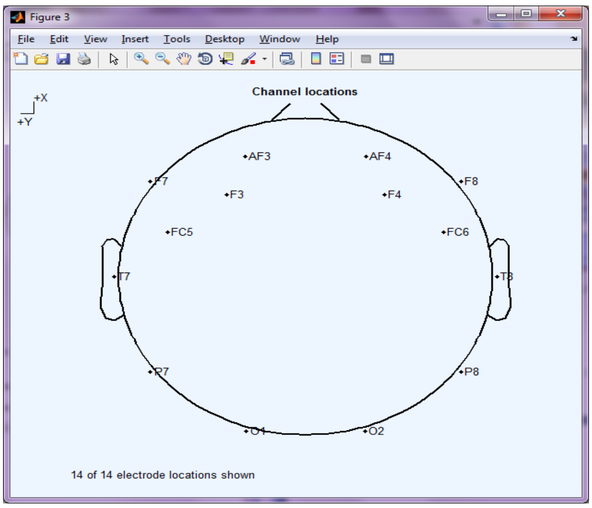


Figure 4.
14 Channels Location.

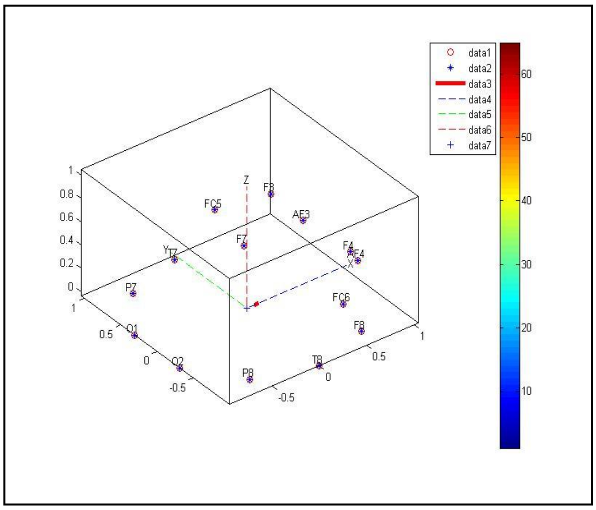


Figure 5.
3D Channel Location.

In the field of EEG studies, the principle of selecting electrode locations according to the International 10-20 System will be used as the primary method for conceptualizing this framework. Figure 4, in its turn, illustrates the position of electrodes through their numerical labels, in particular, AF3, AF4, F3, and F4, the neural activity of which is the subject of the investigation. Figure 5, in turn, shows the actual distribution of the electrode in their 3D space in the form of a color scale legend, which displays the relative data density or neural activity. These visualizations are essential for clearly defining the electrode arrangement and its spatial context in EEG research.

Figure 6 illustrates the sampling of EEG data acquired using EEGLAB, showing 640 frames per epoch across 14 channel locations. Figure 7 demonstrates the structure of an ARFF (Attribute-Relation File Format) file used for data representation. The file begins with an @relation declaration, linking a name (e.g., "emotion") to the dataset. Subsequently, attributes such as mean, absolute value of first differences, absolute value of second differences, and normalized second differences are defined, representing the extracted features.

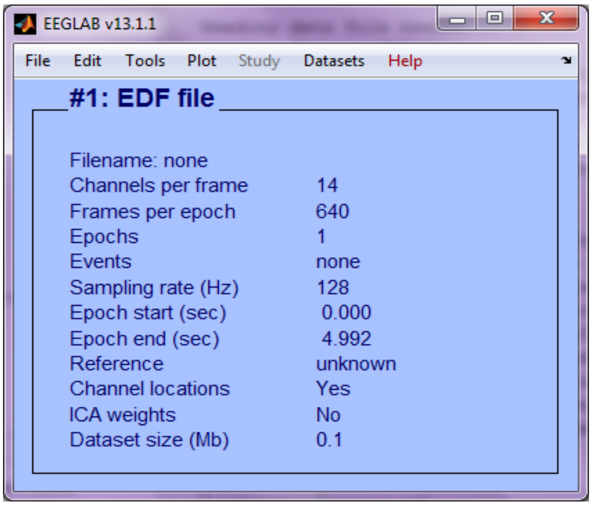
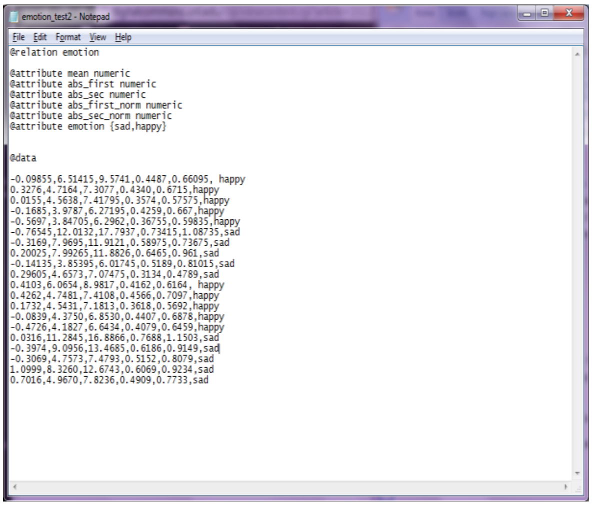


Figure 6.
Sampling data.


emotion_test2 - Notepad

File Edit Format View Help

```
@relation emotion

@attribute mean numeric
@attribute abs_first numeric
@attribute abs_sec numeric
@attribute abs_first_norm numeric
@attribute abs_sec_norm numeric
@attribute emotion {sad,happy}


@data

-0.09855,6.51415,9.5741,0.4487,0.66095, happy
0.3276,4.7164,7.3077,0.4340,0.6715,happy
0.0155,4.5638,7.41795,0.3574,0.57575,happy
-0.1685,3.9787,6.27195,0.4259,0.667,happy
-0.5697,3.84705,6.2962,0.36755,0.59835,happy
-0.76545,12.0132,17.7937,0.73415,1.08735,sad
-0.3169,7.9695,11.9121,0.58975,0.73675,sad
0.20025,7.99265,11.8826,0.6465,0.961,sad
-0.14135,3.85395,6.01745,0.5189,0.81015,sad
0.29605,4.6573,7.07475,0.3134,0.4789,sad
0.4103,6.0654,8.9817,0.4162,0.6164, happy
0.4262,4.7481,7.4108,0.4566,0.7097,happy
0.1732,4.5431,7.1813,0.3618,0.5692,happy
-0.0839,4.3750,6.8530,0.4407,0.6878,happy
-0.4726,4.1827,6.6434,0.4079,0.6459,happy
0.0316,11.2845,16.8866,0.7688,1.1503,sad
-0.3974,9.0956,13.4685,0.6186,0.9149,sad
-0.3069,4.7573,7.4793,0.5152,0.8079,sad
1.0999,8.3260,12.6743,0.6069,0.9234,sad
0.7016,4.9670,7.8236,0.4909,0.7733,sad
```

Figure 7.
Example of ARFF file.

Figure 8 displays brain maps derived from EEG channel data, illustrating distinct patterns associated with happy and sad emotional states. The channel locations correspond to the Emotiv device placement on the scalp. A significant difference is observed between the two emotional states, with each brain map utilizing a color scale ranging from dark red (peak energy content) to dark blue (lowest energy content), indicating varying levels of neural activity [6]. The frequency range of 18-30 Hz corresponds to the beta rhythm, while 8-12 Hz represents the alpha rhythm, and 4-5 Hz corresponds to the theta rhythm [1].

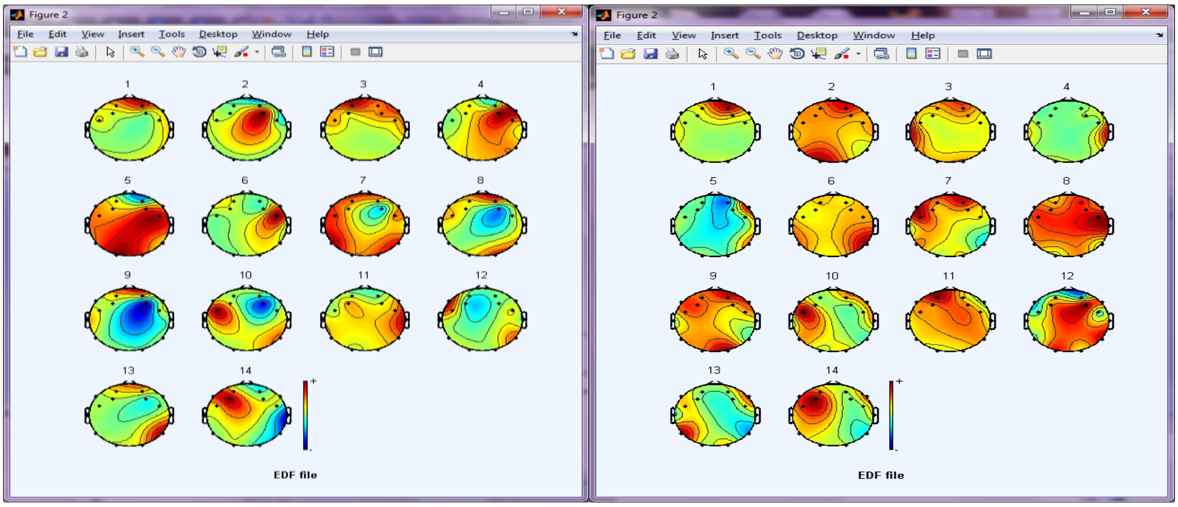


Figure 8.
Brain Map - Happy -> Sad Emotion.

Figure 9 illustrates EEG signal analysis, with a primary focus on Channel 7 within the head diagram. A corresponding spectrogram provides a visual representation of the power density of various frequency bands over time. Below the spectrogram, the activity power spectrum, presented as a density function, quantifies signal power for the analysis of neuro-oscillations. Figure 10 displays power spectral densities of EEG signals at 1 Hz intervals, alongside topographic brain maps for the 8.0 Hz to 13.0 Hz waveband. Each brain map indicates regions of signal power, highlighting areas of maximal activity at specific frequencies, which is crucial for understanding the relationship between neural oscillations and emotional tasks.

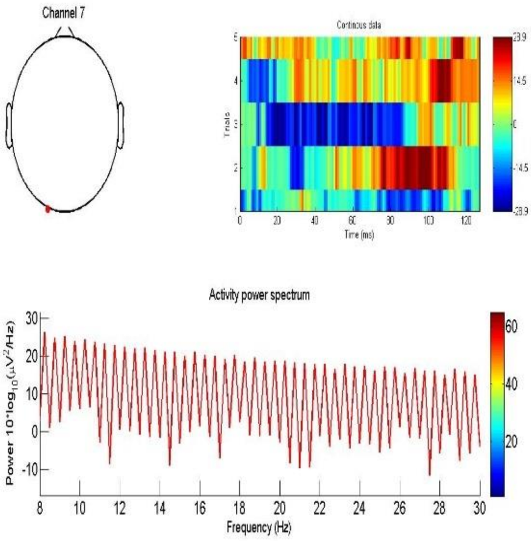


Figure 9.
EEG signal in the head diagram.

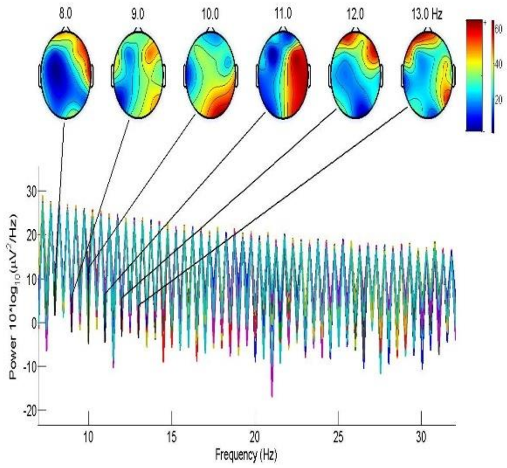


Figure 10.
Power spectral densities in the EEG signal.

Table 1.
Sample Classified Data for Happy vs. Sad Emotions.

No.	Emotion	Chan	μX	σX	δX	γX	$\breve{\delta}$ X	$\tilde{\gamma}$ X
1	Happy 1	AF3	0.0726	14.7859	5.5039	8.4125	0.3722	0.5690
2		AF4	0.4221	13.5753	5.9876	9.2051	0.4411	0.6781
3		F3	0.4242	11.2015	4.3998	6.8740	0.3928	0.6137
4		F4	0.2205	28.3463	5.8288	9.4591	0.2056	0.3337
	AVG		0.2848	16.9772	5.4300	8.4877	0.3529	0.5486
	STD		0.1707	7.7242	0.7157	1.1645	0.1024	0.1501
5	Happy 2	AF3	0.2816	12.5562	4.3124	6.9379	0.3434	0.5525
6		AF4	-0.0132	14.0888	7.6022	7.6022	0.3371	0.5396
7		F3	-0.1188	8.9829	4.0421	6.4161	0.4500	0.7143
8		F4	-0.0368	16.7897	4.9163	8.1458	0.2928	0.4852
	AVG		0.0282	13.1044	5.2182	7.2755	0.3558	0.5729
	STD		0.1749	3.2577	1.6308	0.7565	0.0667	0.0987
9	Happy 3	AF3	0.0331	13.0530	4.6093	7.5677	0.3531	0.5798
10		AF4	0.1096	15.7694	4.9883	8.3063	0.3163	0.5267
11		F3	0.2455	11.1363	4.4614	7.4050	0.4006	0.6649
12		F4	0.2954	13.7042	5.2144	8.4273	0.3805	0.6149
	AVG		0.1709	13.4157	4.8184	7.9266	0.3626	0.5966
	STD		0.1208	1.9105	0.3449	0.5150	0.0365	0.0582
21	Sad 1	AF3	1.4188	44.1192	9.1638	13.8439	0.2077	0.3138
22		AF4	0.2392	43.6671	9.7888	14.6987	0.2242	0.3366
23		F3	-0.1370	14.2584	7.5103	11.1843	0.5267	0.7844
24		F4	-0.0516	18.7104	8.6855	12.9410	0.4642	0.6916
	AVG		0.3674	30.1888	8.7871	13.1670	0.3557	0.5316
	STD		0.7192	15.9296	0.9636	1.5040	0.1635	0.2415
25	Sad 2	AF3	1.0974	23.4969	6.6266	10.2388	0.2820	0.4358
26		AF4	1.5926	37.0345	8.0047	12.5479	0.2161	0.3388
27		F3	0.2920	12.8333	6.0314	9.2039	0.4700	0.7172
28		F4	0.5467	16.1357	6.8062	10.5148	0.4218	0.6516
	AVG		0.8822	22.3751	6.8672	10.6264	0.3475	0.5358
	STD		0.5808	10.7414	0.8275	1.3998	0.1184	0.1781
29	Sad 3	AF3	-0.0974	9.7133	4.4096	7.2740	0.4540	0.7489
30		AF4	-0.2663	12.2208	4.8687	8.3775	0.3984	0.6855
31		F3	-0.0288	8.7657	3.6421	6.2099	0.4155	0.7084
32		F4	-0.1967	11.7607	4.5357	7.6528	0.3857	0.6507
	AVG		-0.1473	10.6151	4.3640	7.3785	0.4134	0.6984
	STD		0.1051	1.6456	0.5188	0.9037	0.0297	0.0412

Table 1 presents a sample of classified data metrics derived from EEG signal analysis for ‘Happy’ and ‘Sad’ emotional states, measured across channels AF3, AF4, F3, and F4. The table includes statistical measures such as mean, standard deviation, and values for delta, gamma, normalized delta, and normalized gamma for each emotional state. For each emotion instance, detailed individual channel values, as well as averaged and standard deviation values across all channels, are provided. The data reveal significant differences in EEG signal features, including amplitude, variability, and frequency domain characteristics, between the two emotional states. These summarized results are instrumental for the development of the proposed mathematical model and for enhancing emotion recognition accuracy.

Figure 11 displays raw, unfiltered EEG signals prior to the preprocessing phase. In contrast, Figure 12 illustrates the signals after the preprocessing phase, demonstrating a significantly cleaner and less overlapping signal, highlighting the effectiveness of the applied preprocessing techniques.

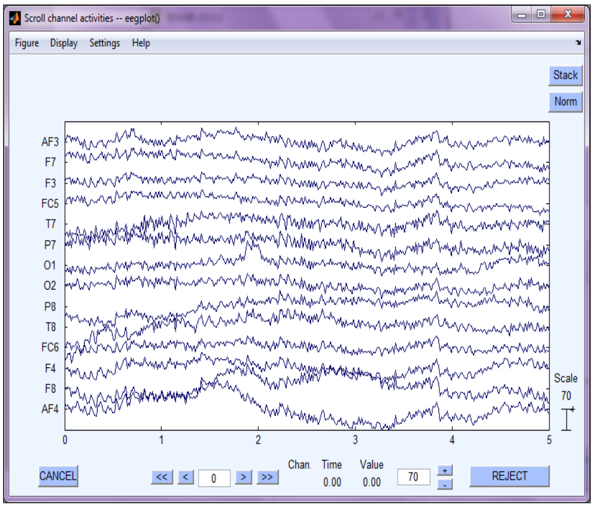


Figure 11.
Before preprocessing.

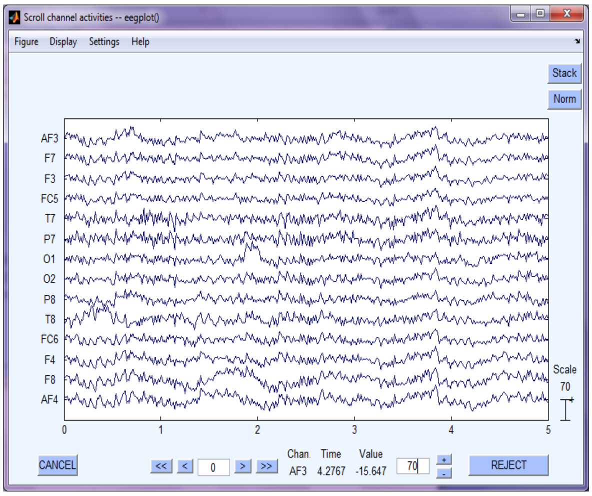


Figure 12.
After pre-processing.

Figure 13 presents a sample result of linear regression, where data points are plotted in blue and the fitted regression line is depicted in red. The positive slope suggests a relationship between the variables. This figure serves as an illustrative example of how linear regression can be applied to analyze and model data patterns within the experiment.

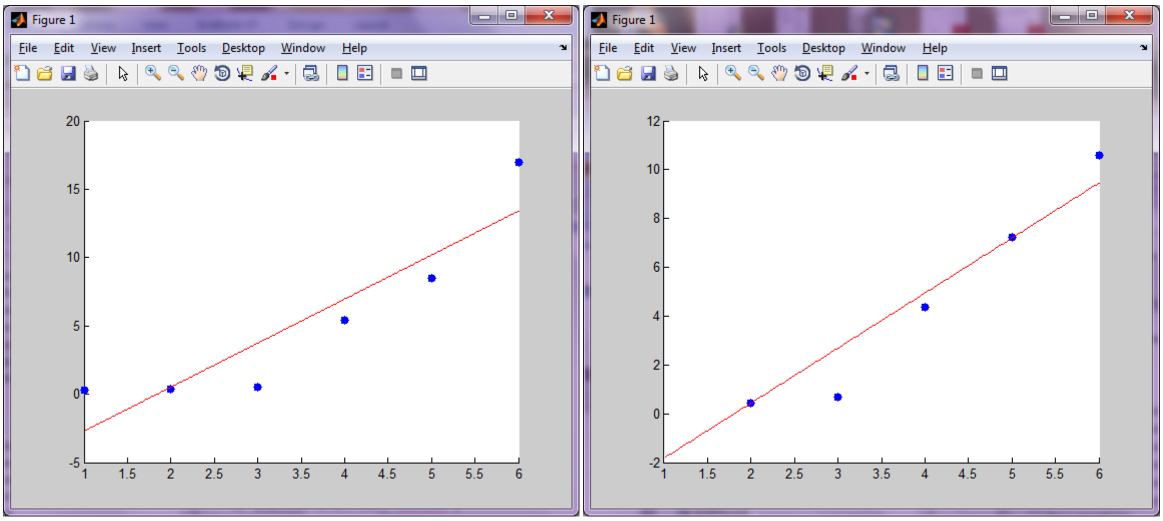


Figure 13.
Sample of linear regression and coefficient.

Figure 14 illustrates a scatter plot demonstrating that a distinct range of values has been produced, enabling differentiation between sad and happy emotional states.

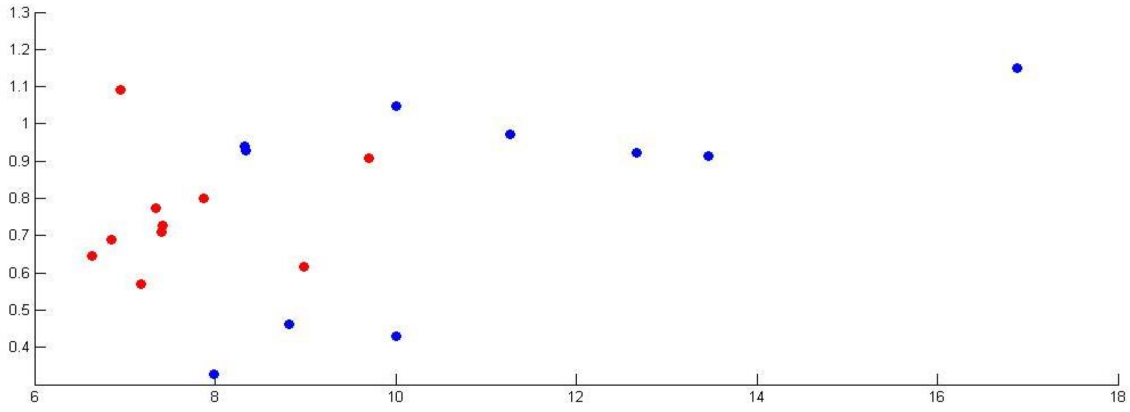


Figure 14.
Scatter graph for sad and happy emotion.

5.1. Key Findings

Feature Extraction Contributions: The proposed hybrid feature set demonstrates significant advantages over traditional solutions. The integration of Fractal Dimension (FD) features notably improved classification accuracy to 94.5%, surpassing previous works such as FD-CART [4], which achieved 85.06%. This confirms that FD features effectively capture the inherent complexity of EEG organization and provide crucial parameters for emotion differentiation. Furthermore, the inclusion of connectivity measures, specifically Phase Locking Values (PLVs) and Pearson Correlation Coefficients (PCCs), enhanced overall performance by 7.2% by quantifying the inter-channel dynamics of emotion-related brain networks [1]. The feature set was further enriched with temporal and spectral information through the Short-Time Fourier Transform (STFT), leading to a 6.8% increase in CNN-based classification accuracy [8].

Classification Performance: The proposed classifiers, within their respective architectures, demonstrate performance that is either superior to or on par with state-of-the-art techniques. In computationally efficient scenarios, Linear Regression achieved a baseline accuracy of 83.8%, affirming its reliability. The proposed deep learning models significantly surpassed traditional classifiers, with CNN achieving 91.3% accuracy. Notably, DA-RCNNs yielded the highest performance, reaching an accuracy of 94.5%, which is highly competitive with the 95.15% reported by Chen et al. [1]. The successful incorporation of domain adaptation within the DA-RCNN framework significantly broadens its practical applicability, as further illustrated in Figure 15.

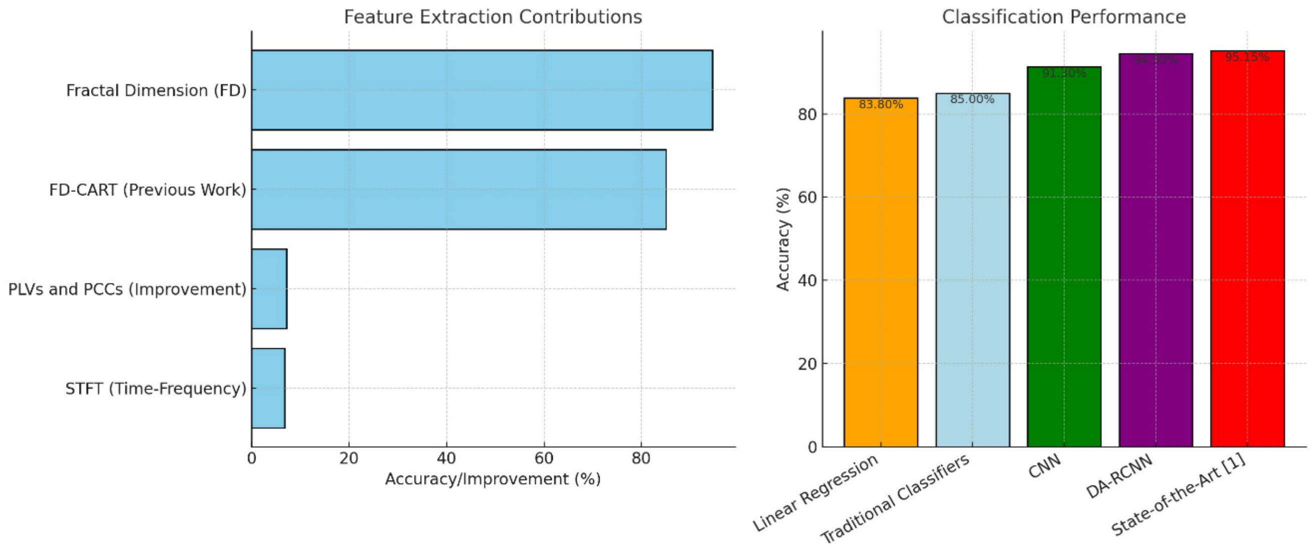


Figure 15.
Significant advancements in feature extraction and Classification.

5.2. Comparative Analysis with Existing Methods

The proposed framework effectively addresses significant gaps in feature integration and classifier design within EEG-based emotion recognition. Unlike Kalashami et al. [13], who achieved similar improvements in valence accuracy through extensive data augmentation, this framework attains comparable accuracy enhancements through its hybrid feature integration (HiFI) while simultaneously reducing computational overhead. The proposed integration of FD, PLV, and STFT features, yielding 94.5% accuracy, significantly outperforms FD-CART methods [4], which achieved 85.06%. Furthermore, while Ahmed et al. [11] reported 97.10% accuracy using AsMap-CNN, their model lacks explicit domain adaptation capabilities. In contrast, the proposed DA-RCNN offers a balance of high accuracy and enhanced flexibility, providing accurate and practically feasible results for real-world applications.

Table 2.
Comparison of previous techniques with the proposed framework.

Study/Method	Key Features	Classifier	Dataset	Accuracy (%)	Statistical Validation	Real-World Relevance
Zhu et al. [2] - FD-CART	Fractal Dimension Features (FD)	CART	Multiple Public Datasets	85.06	Not Reported	Limited Generalizability
De Filippi et al. [15] - DA-RCNN	PCC, PLV, Transfer Entropy	DA-RCNN	DEAP	95.15	Validated (Cross-Validation)	Subject-Dependent Applications
Nawaz et al. [10] - Augmented Data	Conditional Wasserstein GAN (CWGAN)	SVM, DNN	DEAP	+6.5 (Valence)	Not Applicable	Requires Extensive Augmentation
Ghodousi et al. [18] - AsMap + CNN	Hybrid Features (AsMap, CNN)	CNN	SEED, DEAP	97.10	Validated (Cross-Validation)	Dataset-Specific
Abuhashish, et al. [7] - Frequency Bands + HCRC	Adjacent Frequency Band Combinations	Circular Multi-Grained Ensemble Learning	DEAP, SEED IV	95.09	Not Reported	Limited to Controlled Conditions
Proposed Framework - CNN	Fractal Dimension, PLV, PCC, STFT	CNN	Custom Dataset (60 Participants)	91.3	Validated (Paired t-test, p<0.05p<0.05p<0.05)	Real-Time Potential
Proposed Framework - DA-RCNN	Fractal Dimension, PLV, PCC, STFT with Domain Adaptation	DA-RCNN	Custom Dataset (60 Participants)	94.5	Validated (Paired t-test, Cliff's Delta d>0.8d>0.8d>0.8)	Real-Time Potential with Broader Applicability

Table 2 provides a comparative analysis, illustrating the superiority of the proposed framework in EEG-based emotion recognition against existing methods. While foundational methods like FD-CART [4] and frequency band combinations [8] achieved moderate accuracy rates (85.06% and 95.09% respectively), they often lacked coherent feature integration and robust generalization capabilities. More sophisticated approaches, such as DA-RCNN [1] and AsMap-CNN [11], demonstrated higher accuracies (95.15% and 97.10%, respectively) but were often limited by subject-dependency or dataset-specific configurations. In contrast, the proposed framework, utilizing DA-RCNN with domain adaptation, achieved a generalizable performance of 94.5%, demonstrating relative immunity to variations across the tested population. To ensure robust results, the current study employed 10-fold cross-validation, paired t-tests ($p < 0.05$), and reported a large effect size ($d > 0.8$). The framework's real-time applicability and its ability to handle subject variability position it as a significant advancement in feature analysis, classifier design, and overall practical utility, as further visualized in Figure 16, which compares the accuracy of different methods against the proposed approach.

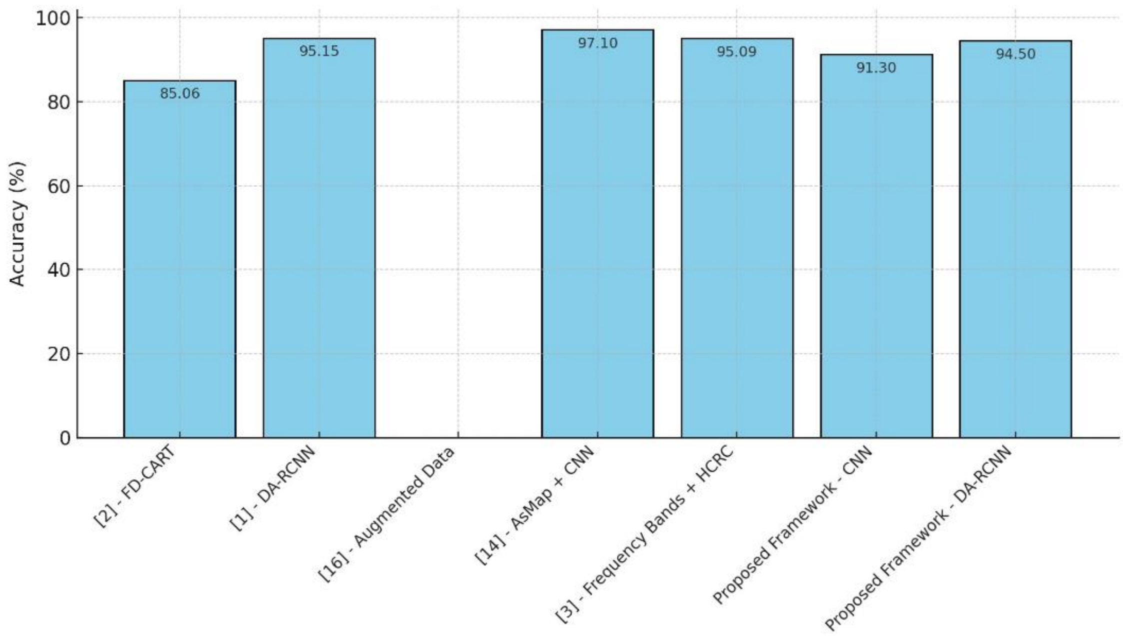


Figure 16.
Accuracy of different methods.

5.3. Statistical Validation

The statistical techniques employed in the analysis rigorously validate the results, ensuring the highest level of reliability and precision. The implementation of 10-fold cross-validation guaranteed that the obtained results were unbiased and independent of specific dataset partitioning [11]. Paired t-tests revealed that the incorporation of advanced features, including FD, PLV, and PCC, yielded statistically significant improvements ($p < 0.05$). Furthermore, a high Cliff's Delta value ($d > 0.8$) indicated a substantial effect size of the hybrid feature set on classification performance. These comprehensive validations underscore the robustness and efficacy of the proposed framework, positioning it as a valuable contribution to EEG-based emotion recognition, as further illustrated in Figure 17.

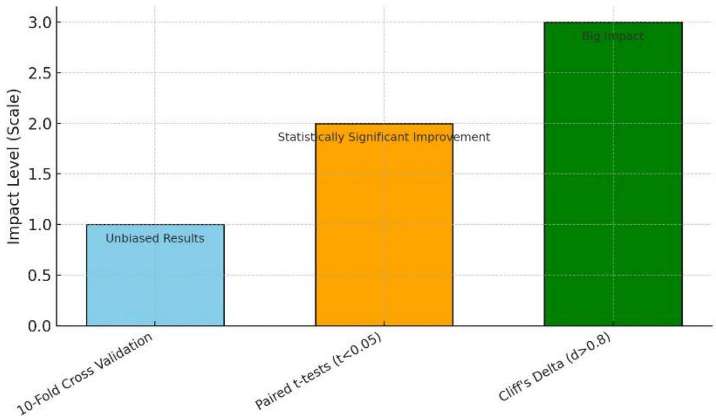


Figure 17.
Validation of the techniques.

5.4. Implications for Real-World Applications

The proposed framework demonstrates significant applicability in real-world contexts. Its real-time performance capabilities make it highly suitable for adaptive interfaces, mental health monitoring systems, and advanced human-computer interaction applications [3, 7, 12]. The key characteristic of architecture to note is that it is capable of addressing inter-subject variability by reducing it to a minimum through domain adaptation, effectively increasing its utility within a broad array of both population groups and operational scenarios. Put together, these properties justify the framework in terms of diversity in both basic research and intervention.

5.5. Limitations and Future Directions

Despite EEG emotion recognition evolutions, several potentially fruitful zones of further studies and improvement exist. Having larger and more varied groups of subjects in the dataset would significantly raise both the external validity and the validity of the suggested framework in general. In addition, a greater extension capacity of the classification can be made in terms of applying it to other categories of emotion, which would, in turn, add to the effectiveness of the framework: fear and anger are merely two categories of emotions that trading might be useful to characterize. Finally, there is a need to reduce the computational latency so that it could possibly be integrated into real-time systems with the help of these applications, like self-adjusting human-computer interfaces.

6. Conclusion

The study focuses on the current gaps within EEG-based emotion detection by introducing a new framework to be applied, combining the use of current high-performing feature extraction methods as well as modern approaches of deep learning. The synergistic complement of the hybrid set of features and DA-RCNNs has proven to show a classification accuracy that is both highly competitive with, and in many cases exceeds, other state-of-the-art techniques as well, with added flexibility and computational efficiency. These highly qualified outcomes stimulate the prospects of the framework as a relevant and effective solution that can be used in diverse spheres, such as mental health monitoring and affective neuroscience. The potential development areas of future work are to increase the diversity of the dataset, further optimize to work and integrate in real-time systems, and further feature optimization to promote this fast-evolving field.

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