Affective Computing for Emotion Recognition

Using EEG Signals

A

report submitted in partial fulfillment for the award of the degree of

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By

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Under the Supervision of

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DECLARATION

I hereby certify that the work, which is being presented in the report/thesis, entitled Affective Computing for Emotion Recognition Using EEG Signals, in fulfillment of the requirement for the award of the degree of Bachelor of Technology and submitted to the institution is an authentic record of my/our own work carried out during the period May-2024 to July-2024 under the supervision of Dr.Anjali. I also cited the reference about the text(s)/figure(s)/table(s) from where they have been taken.

Dated: **Signature of the candidate**

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Dated: **Signature of supervisor**

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Muthiah Sivavelan

Abstract

In this study, we utilize the publicly available DREAMER database, which includes data for nine distinct emotions, to develop a deep learning-based Convolutional Neural Network (CNN) model. Initially, EEG signals are decomposed into theta, alpha, beta, and gamma frequency bands through Discrete Wavelet Transform (DWT). Subsequently, Empirical Mode Decomposition (EMD) is applied to further decompose these band-separated signals into Intrinsic Mode Functions (IMFs). From these IMFs, 31 statistical features are extracted to build a machine learning-based system using five multiclass ensemble learning algorithms, such as bagging.

The study also explores the effectiveness of deep learning models, including CNN and Recurrent Neural Networks (RNN), with the addition of attention mechanisms to enhance emotion classification. We evaluate the performance of these models using 5-fold cross-validation to ensure robust results. Pre-processing and feature extraction phases are crucially implemented to reduce noise and obtain more informative data. The CNN model, equipped with a modified architecture, achieved a classification accuracy of 90.58% across the nine emotions. Multiple parametric and comparative experiments were conducted to validate these findings.

Keywords: *EEG Signals, Emotion Recognition, Deep Learning, Convolutional Neural Network, Recurrent Neural Network, Discrete Wavelet Transform, Empirical Mode Decomposition, Intrinsic Mode Functions, Ensemble Learning, Attention Mechanisms, DREAMER Database, Feature Extraction, 5-Fold Cross-Validation, Multiclass Classification*

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1 Introduction

This chapter offers an overview of the subject matter by presenting background information on cognitive radio networks and emphasizes the potential of deep reinforcement learning. Moreover, this chapter entails the motivating factors that instigated the investigation of this topic.

1.1 Introduction

Human emotion recognition is crucial for enhancing human-machine interactions, allowing systems to respond more intuitively to human emotional states. Emotions are closely tied to psychological and physiological conditions, with electroencephalography (EEG) signals providing a reliable means of detecting these emotions. Unlike other signals, EEG is controlled by the autonomic nervous system, making it less susceptible to subjective biases and offering a direct measure of the brain's cortical electrical activity. This makes EEG a valuable source of authentic information about various mental states.

Emotions can generally be categorized into two groups: (i) discrete emotions such as surprise, fear, joy, sadness, anger, and disgust, and (ii) multi-dimensional emotions that include arousal and valence dimensions. The arousal dimension indicates the intensity of emotions, ranging from passive to active, while the valence dimension represents the positivity or negativity of the emotion.

1.2 Emotion Recognition using Machine Learning and Deep Learning Sensing

In recent years, advancements in artificial intelligence (AI), particularly in machine learning (ML) and deep learning (DL), have increasingly been applied to EEG-based emotion recognition. These AI-based approaches typically involve a two-step process: (i) extracting features from EEG signals and (ii) classifying these features into specific emotional states using ML or DL models. Initially, EEG signals are decomposed into frequency bands—such as alpha, beta, gamma, and theta—using various methods like band-pass filtering, short-time Fourier transform (STFT), discrete wavelet transform (DWT), and empirical mode decomposition (EMD). Features are then extracted from these band-separated signals for emotion classification.

While traditional ML models require manual feature extraction, deep learning models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can automatically learn features from raw data, often leading to improved classification accuracy. This study explores the potential of deep learning models, specifically CNN and RNN architectures, in directly classifying nine distinct emotions from EEG signals. By transitioning from traditional methods to deep learning, this study aims to achieve higher classification accuracy and offer a more comprehensive perspective on EEG-based emotion recognition, moving beyond the conventional focus on valence and arousal dimensions.

Our approach achieved an accuracy of approximately 90.56%, demonstrating the effectiveness of deep learning in overcoming the limitations of traditional methods. Unlike most studies that focus on valence and arousal, our approach classifies a broader set of emotions, providing a new perspective on EEG-based emotion recognition and highlighting the potential of deep learning to address the challenges of traditional methods.

For instance, Cimtay et al. used a convolutional neural network (CNN) to extract the spatial features of emotional activities, achieving accuracies of 86.56% and 72.81% on the SEED and DEAP datasets, respectively [?]. Wang et al. extended the dimension of CNN and designed EmotioNet to obtain spatial features [?]. Alhagry et al. utilized long short-term memory (LSTM) networks to represent temporal features from EEG signals, achieving classification accuracies of 85.65% for arousal and 85.45% for valence on the DEAP dataset [?]. Additionally, Ma et al. proposed a multimodal residual LSTM (MMResLSTM) network containing temporal shortcut paths to extract temporal representations [?]. Yang et al. proposed hybrid neural networks combining a CNN and an RNN to learn both spatial and temporal representations of EEG signals, achieving high performance with mean accuracies of 90.80% and 91.03% for valence and arousal emotion classification, respectively [?].

1.3 Motivation

A significant body of research has focused on decomposing EEG signals using methods like Empirical Mode Decomposition (EMD) to extract features that can be used for emotion classification. Many studies have employed a single popular method, such as EMD, for EEG signal decomposition, followed by feature extraction to recognize emotions. Some researchers have integrated Discrete Wavelet Transform (DWT) with EMD to achieve better decomposition of EEG signals. DWT is particularly effective in converting multiband EEG signals into sequences of narrow-band signals, thereby supporting EMD in generating Intrinsic Mode Functions (IMFs) with more concentrated frequency components. While dual decomposition approaches such as DWT followed by EMD or EMD followed by DWT have shown promise, they still face limitations in providing accurate emotion recognition.

Recognizing these challenges, this study initially applied DWT and EMD separately before extracting statistical features from EEG signals. However, this approach did not yield satisfactory accuracy. To address this, we employed deep learning models, including Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), which automatically learn features from data. This shift resulted in a significant improvement, with an accuracy of approximately 90.56% in classifying nine distinct emotions directly.

In conclusion, our approach provides a broader perspective on EEG-based emotion recognition and highlights the potential of deep learning to overcome the limitations of traditional methods, such as manual feature extraction and the narrow focus on valence and arousal dimensions. This work underscores the importance of continued exploration of deep learning models for more comprehensive and accurate emotion recognition systems.

2

A Review on Advances in EEG-Based Emotion Recognition

This chapter addresses the significant advancements in EEG-based emotion recognition, focusing on the evolution of signal decomposition methods and the integration of machine learning and deep learning techniques. We examine the literature on traditional approaches like Empirical Mode Decomposition (EMD) and Discrete Wavelet Transform (DWT) and explore the shift toward deep learning models that have improved classification accuracy. The chapter highlights key studies and identifies research gaps, paving the way for further advancements in emotion recognition from EEG signals.

2.1 Review of EEG Signal Decomposition Techniques for Emotion Recognition

EEG-based emotion recognition has seen significant advances due to the application of various signal decomposition methods and machine learning (ML) algorithms. One prominent method is Empirical Mode Decomposition (EMD), which has been widely used for feature extraction from EEG signals. EMD helps in breaking down EEG signals into Intrinsic Mode Functions (IMFs) that can be used for emotion classification. Despite its popularity, using EMD alone often results in limitations regarding emotion recognition accuracy [1].

To address these limitations, researchers have explored integrating other decomposition techniques, such as Discrete Wavelet Transform (DWT), with EMD. DWT is particularly effective in converting multiband EEG signals into sequences of narrow-band signals, which aids in generating IMFs with more concentrated frequency components when combined with EMD. While dual decomposition approaches like DWT followed by EMD or EMD followed by DWT have shown promise, these techniques still struggle to achieve highly accurate emotion recognition [2].

2.2 Advances in Machine Learning and Deep Learning Approaches

In response to these challenges, many studies have shifted towards deep learning models. Deep learning techniques such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) offer an alternative by automatically learning features from the data, resulting in higher accuracy. For instance, Cimtay et al. [3] used a CNN to extract spatial features from emotional activities, achieving accuracies of 86.56% and 72.81% on the SEED and DEAP datasets, respectively. Wang et al. [4] extended the CNN architecture to design EmotioNet, which further improved spatial feature extraction. Alhagry et al. [5] leveraged Long Short-Term Memory (LSTM) networks to capture temporal features from EEG signals, achieving classification accuracies of 85.65% for arousal and 85.45% for valence on the DEAP dataset. Ma et al. [6] proposed a multimodal residual LSTM (MM-ResLSTM) network, which incorporated temporal shortcut paths to improve temporal representations. Yang et al. [7] introduced a hybrid neural network combining CNN and RNN to learn both spatial and temporal representations of EEG signals, with mean accuracies of 90.80% and 91.03% for valence and arousal emotion classification, respectively.

2.3 Comparative Analysis of Traditional and Modern Methods

Recent studies have continued to adopt this two-tier framework for EEG-based emotion recognition. For example, Lakhan et al. [8] proposed an EEG-based emotion recognition system that employed the SVM algorithm to classify emotions based on power spectral density features extracted from band-separated EEG signals, with an overall classification accuracy of 67.4% for arousal and 66.67% for valence emotions. Sharma and Bhattacharyya [9] utilized sliding mode singular spectrum analysis for EEG decomposition and the K-Nearest Neighbors (KNN) algorithm for predicting human emotional states, achieving an overall classification accuracy of 92.38%. Zheng and Lu [10] investigated critical frequency bands and channels for EEG-based emotion recognition with deep neural networks, highlighting the importance of specific EEG features. Koelstra et al. [11] introduced the DEAP dataset for emotion analysis using physiological signals, providing a valuable resource for developing and evaluating emotion recognition systems.

3

Problem Statement based on Identified Research Gaps

This chapter explains the formulation of the problem that this thesis addresses, as well as it outlines the thesis objectives.

3.1 Problem Formulation

In the domain of EEG-based emotion recognition, previous research has predominantly centered on conventional feature extraction methods and machine learning algorithms. Traditional approaches, such as those relying solely on Empirical Mode Decomposition (EMD) or Discrete Wavelet Transform (DWT), often encounter limitations in achieving high emotion classification accuracy. These methods have been beneficial but fall short in handling complex and nuanced emotional states.

To address these issues, it is essential to explore and integrate advanced deep learning techniques that can offer improved performance and accuracy. Specifically, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) present promising avenues for enhancing emotion recognition systems. The focus of future research should include:

- **Integration of Deep Learning Models:** Leveraging CNNs and RNNs to automatically learn and extract features from EEG signals, providing a significant boost in classification accuracy.

- **Hybrid Approaches:** Combining traditional decomposition techniques with modern deep learning models to enhance the robustness and accuracy of emotion classification.

- **Broad Emotion Classification:** Extending beyond basic valence and arousal dimensions to classify a broader range of emotions, such as amusement, anger, and surprise, for a more comprehensive emotion recognition system.

- **Evaluation and Validation:** Applying these advanced methods to diverse datasets to assess their effectiveness and generalizability across different emotional states and subjects.

3.2 Thesis Objective

- To review and analyze existing methods for EEG-based emotion recognition, focusing on both traditional signal decomposition techniques and modern deep learning approaches.
- To integrate Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) for enhanced feature extraction from EEG signals, aiming to improve classification accuracy.
- To implement deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to classify a broad range of emotions from EEG data.
- To evaluate the performance of these models by comparing their accuracy in emotion classification against traditional methods and assessing their effectiveness across different datasets.
- To explore and address the challenges and limitations in EEG-based emotion recognition, providing recommendations for future research directions and potential improvements.

4

Proposed Methodology

This chapter details the methodology utilized in this study for EEG-based emotion recognition. It includes a thorough examination of the signal processing techniques, such as Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD), as well as the deep learning models employed.

4.1 Study flow

Development in machine learning and artificial intelligence heavily relies on identifying the most effective solutions for emerging challenges by drawing insights from current methodologies. In the context of emotion recognition using EEG signals, various approaches and techniques have been explored.

There are two primary categories of reinforcement learning algorithms: model-based and model-free. Model-based algorithms employ a model of the environment to anticipate the outcome of actions, while model-free algorithms learn the optimal policy without a model. The proposed study methodology includes several stages, as illustrated in Fig. 1. The dataset used in this research is the DREAMER database, which encompasses both EEG and ECG signals along with target information such as EEG-based emotions, arousal, valence, and dominance. The dataset comprises signals from 23 participants, with each participant's EEG data recorded for 60 seconds while viewing videos, resulting in varied lengths of video stimuli.

The initial stage involves data preprocessing and analysis, where the dataset's EEG signals, recorded from 14 electrodes, are prepared. Subsequently, the dataset is split into training and validation and test sets using an 80:10:10 ratio, using 5-fold cross validation. To extract meaningful features from the EEG signals, Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) are applied. DWT decomposes the signals into alpha, beta, gamma, and theta bands, while EMD provides 7 Intrinsic Mode Functions (IMFs) for each of the 14 electrodes. In addition, 31 statistical features are extracted using ANOVA.

The processed data, including features obtained from DWT, EMD, and statistical analyses, are fed into machine learning models such as XGBoost and Random Forest for classification. Additionally, the raw EEG signals are directly input into Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) separately.

This diagram Fig 4.1 demonstrates the flow of data(observation, action and reward) used to update the policy. The policy is then used to decide and action.

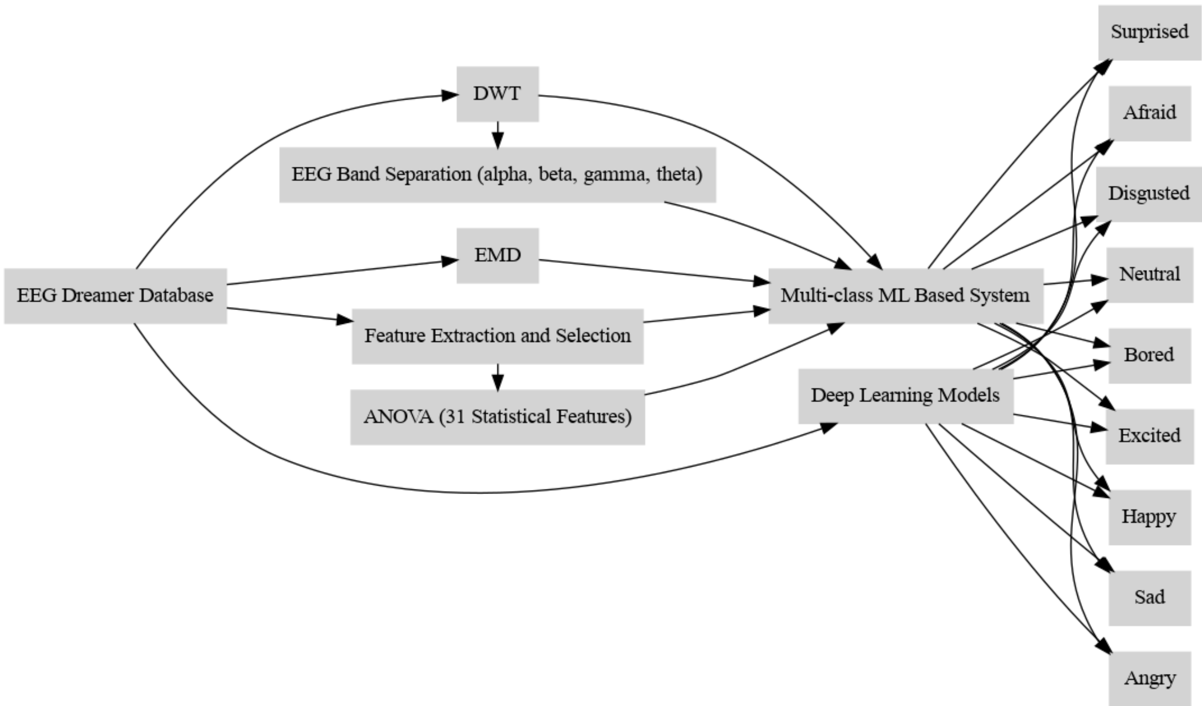


Figure 4.1: Project Layout

4.2 Methodologies used

The approach in this study leverages feature extraction techniques including DWT and EMD, along with machine learning and deep learning models, to classify emotions from EEG signals with high accuracy.

- Discrete Wavelet Transform (DWT)
- Empirical Mode Decomposition (EMD)
- Statistical Features
- XGBoost
- Random Forest
- Recurrent Neural Networks (RNN)
- Convolutional Neural Networks (CNN)

4.2.1 Discrete Wavelet Transform (DWT)

Discrete Wavelet Transform (DWT) is a powerful technique used for analyzing and decomposing signals into various frequency components. DWT separates a signal into different frequency bands, which helps in understanding its structure at multiple resolutions. This technique is particularly useful for capturing both time and frequency information, making it suitable for analyzing non-stationary signals such as EEG.

In EEG signal analysis, DWT is used to decompose the signal into different frequency bands, including alpha, beta, gamma, and theta. Fig. 4.2 represents the general schema for DWT. These frequency bands correspond to various brain wave patterns and are essential for understanding different cognitive and emotional states [12].

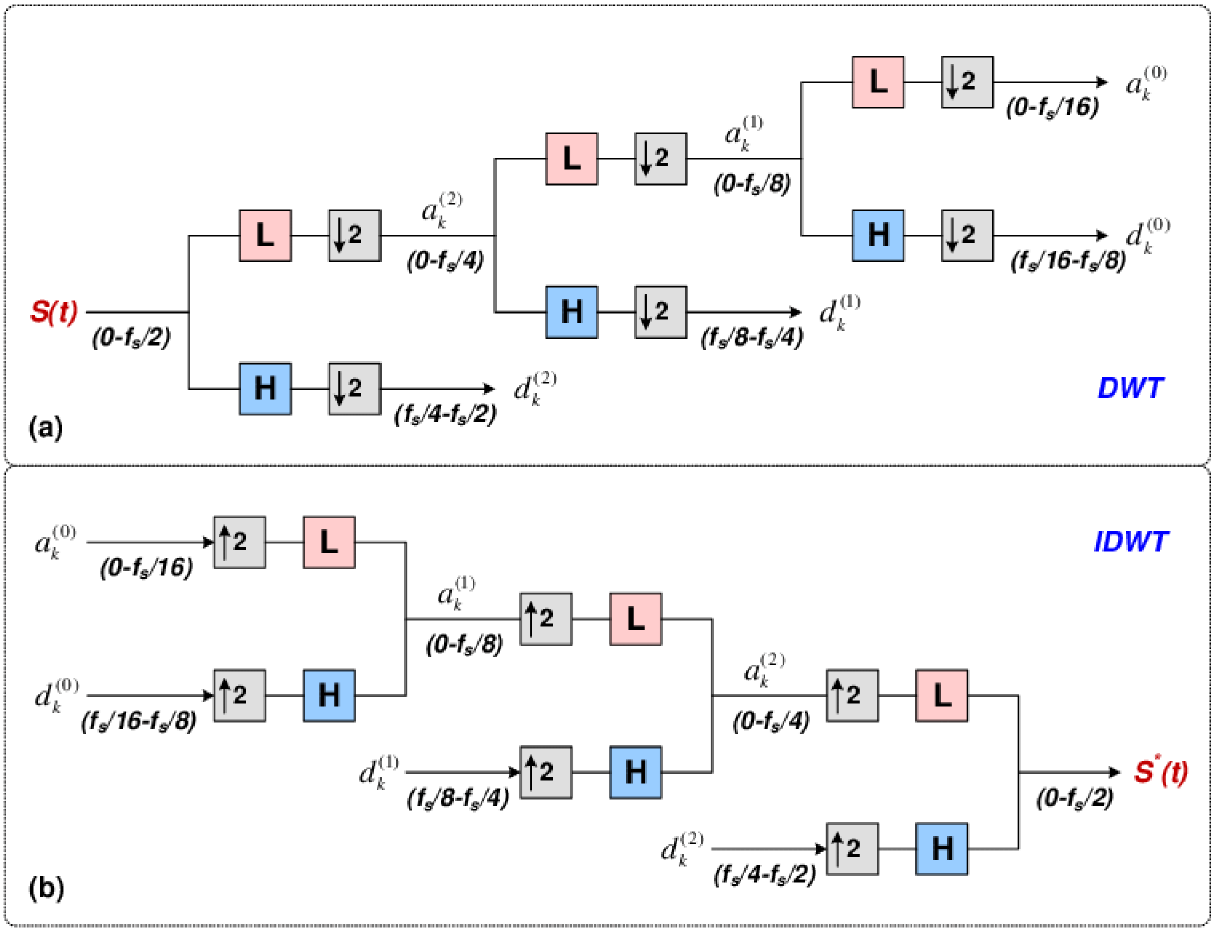


Figure 4.2: DISCRETE WAVELET TRANSFORM SCHEMA

4.2.2 Empirical Mode Decomposition (EMD)

Empirical Mode Decomposition (EMD) is a powerful signal processing technique used to decompose a signal into its intrinsic mode functions (IMFs) and a residual trend. Unlike traditional transforms that require a predefined basis function, EMD is adaptive and works directly on the signal to extract components based on its intrinsic characteristics. This makes EMD particularly effective for analyzing non-stationary and nonlinear signals, such as EEG data.

In the context of EEG signals, EMD helps to decompose the data into multiple IMFs, each representing different oscillatory modes. This decomposition provides a detailed representation of various signal components, which can be crucial for identifying distinct brainwave patterns associated with different cognitive and emotional states. By analyzing these IMFs, researchers can extract features that are representative of the underlying processes in the brain, thus improving the accuracy of emotion and state classification. Fig.4.3 represents different IMFs diagrams for a given EEG signal.

For example, EMD can separate EEG signals into components corresponding to different frequency bands or specific brain activities, facilitating a more nuanced analysis of mental states. This adaptability and ability to capture complex patterns make EMD a valuable tool for EEG signal processing [13].

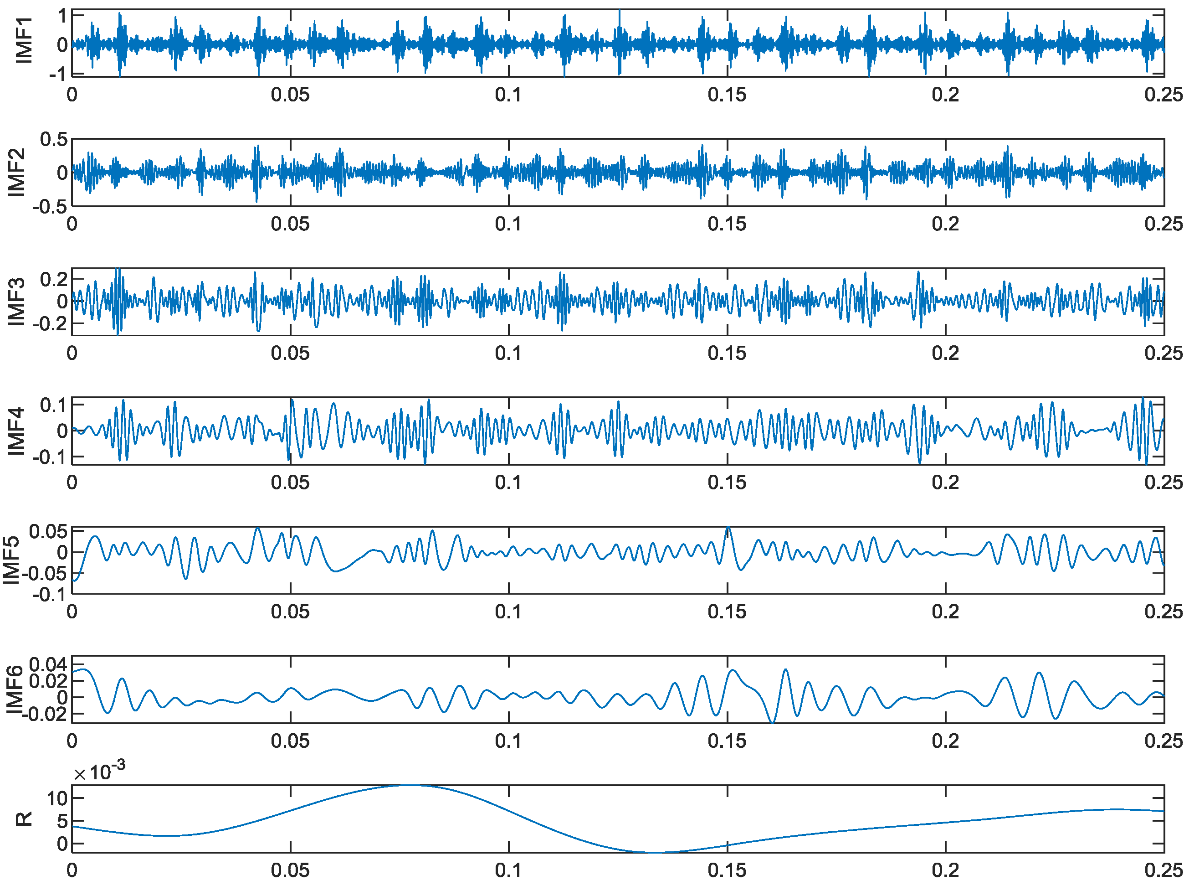


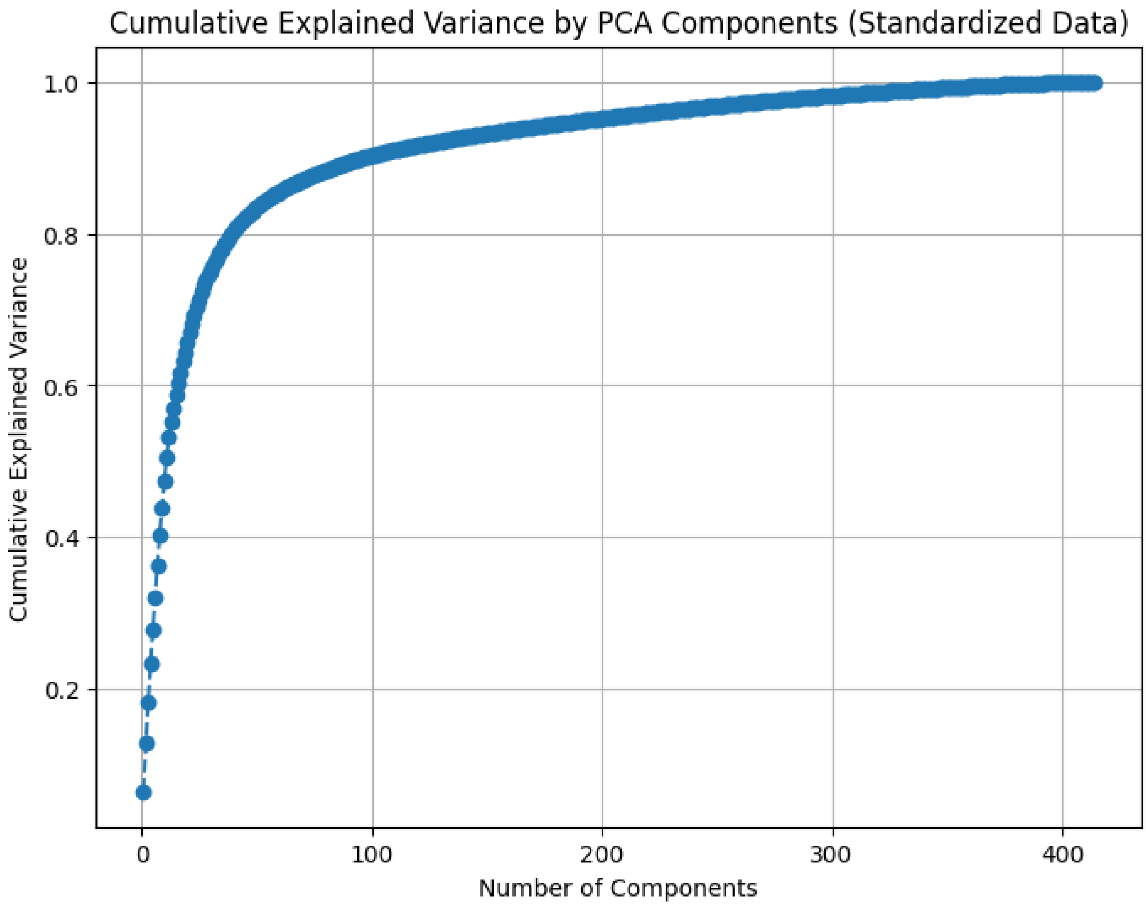
Figure 4.3: Empirical Mode Decomposition (EMD)

4.2.3 Statistical Features (ANOVA)

ANOVA, or Analysis of Variance, is a statistical method used to compare means across multiple groups to determine if there are significant differences between them. In the context of feature extraction for EEG signals, ANOVA is used to identify which features contribute most significantly to distinguishing between different emotional states or other classes. By analyzing the variance within and between groups of EEG signal features, ANOVA helps in selecting the most relevant features that improve the performance of machine learning models. This technique is crucial in reducing dimensionality and focusing on features that have the highest impact on classification accuracy. Fig. 4.4 represents all the statistical features used in this study for ANOVA. Fig. 4.5 represents the cumulative variance explained by PCA. For instance, ANOVA can reveal which statistical measures of EEG signals, such as mean or variance, differ significantly across different emotional states, thus aiding in effective feature selection for emotion recognition systems [14]).

Rank	Features	p-value
1	Variance	<0.0001
2	Mean Absolute Deviation	<0.0001
3	Mean Absolute Value	<0.0001
4	Modified Mean Absolute Value	<0.0001
5	Modified Mean Absolute Value2	<0.0001
6	Root Mean Square	<0.0001
7	Standard Deviation	<0.0001
8	Inter Quartile Range	<0.0001
9	Median Absolute Deviation	<0.0001
10	Enhanced Mean Absolute Value	<0.0001
11	Log Detector	<0.0001
12	Willison Amplitude	<0.0001
13	Myopulse Percentage Rate	<0.0001
14	Entropy	<0.0001
15	Kurtosis	<0.0001
16	Minimum	<0.0001
17	Maximum	<0.0001
18	Maximum Fractal Length	<0.0001
19	Enhanced Wavelength	<0.0001
20	Difference Absolute STD Value	<0.0001
21	Log Energy Entropy	<0.0001
22	Average Amplitude Change	<0.0001
23	Zero Crossing	<0.0001
24	Wavelength	<0.0001
25	Slope Sign Change	<0.0001
26	Simple Square Integral	0.002
27	Skewness	0.361
28	Mean	0.442
29	Covariance	0.454
30	Median	0.860
31	Shanon Entropy	0.983

Figure 4.4: Statistical Features (ANOVA)




```
Number of components to retain 99.99% variance: 412
```

Figure 4.5: Cumulative PCA explaining the variance of the dataset

4.2.4 XGBoost

XGBoost, or Extreme Gradient Boosting, is a powerful machine learning technique used for classification and regression tasks. It improves upon traditional gradient boosting by incorporating optimizations such as regularization, handling missing values, and parallel processing to enhance model performance and computational efficiency. XGBoost builds an ensemble of decision trees, where each new tree corrects errors made by the previous ones, resulting in high predictive accuracy and robustness against overfitting. In Fig. 4.6, we see the general architecture of the model. XGBoost's efficiency and effectiveness make it a popular choice for various data science challenges [15].

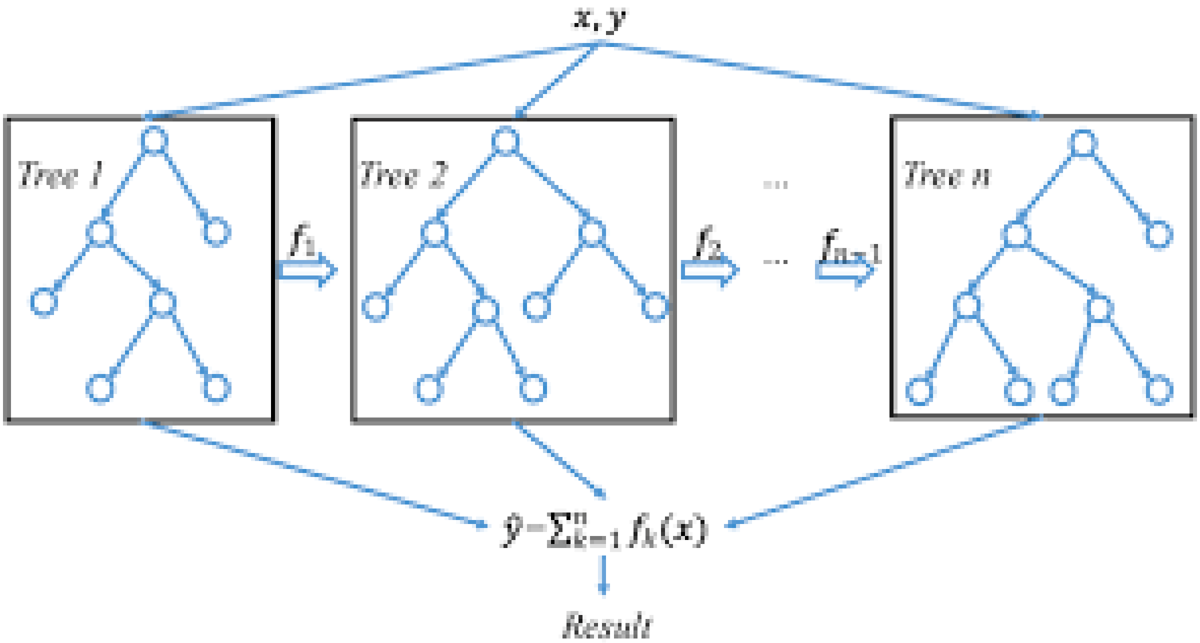


Figure 4.6: XGBoost

4.2.5 Random Forest

Random Forest is an ensemble learning technique that constructs a multitude of decision trees during training and outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. This method improves the predictive accuracy and controls over-fitting by averaging multiple deep decision trees, which reduces variance and helps in handling complex datasets. The model combines the results from various trees to enhance robustness and accuracy compared to a single decision tree. Fig. 4.7 represents the general working of Random Forest. This technique is particularly useful for classification problems and can handle large datasets with numerous features. [16]

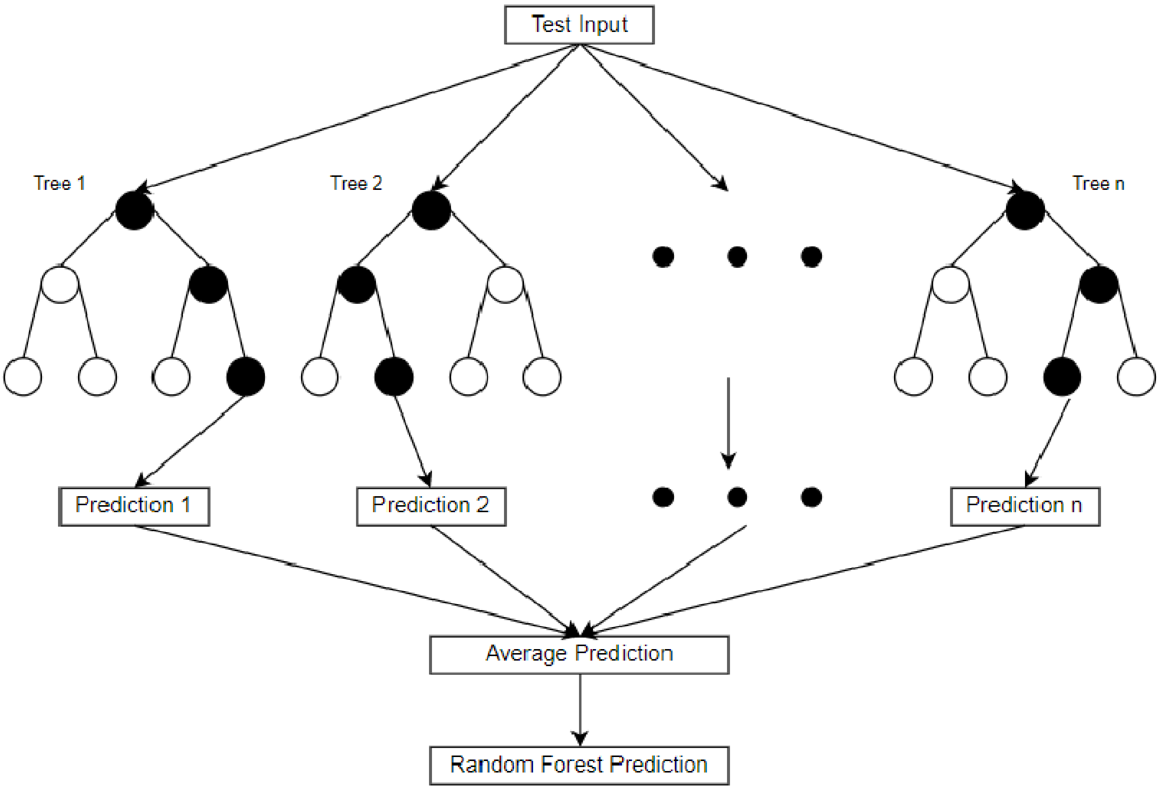


Figure 4.7: Random Forest

4.2.6 Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNN) are a class of neural networks designed for processing sequences of data by maintaining a form of memory. Unlike traditional feedforward neural networks, RNNs have connections that form directed cycles, allowing information to persist. This architecture is particularly suited for tasks where the context or order of the data is important, such as time series analysis or natural language processing. Fig. 4.8 represents the architecture of the RNN model used along with attention mechanism. This model, technically overfitted the data extracting all the temporal dependencies of EEG signals. RNNs can capture temporal dependencies by passing information from previous steps to future steps, enabling them to model sequential data effectively [17].

```
class Attention(nn.Module):
    def __init__(self, hidden_size):
        super(Attention, self).__init__()
        self.hidden_size = hidden_size
        self.attention_weights = nn.Parameter(torch.Tensor(hidden_size, 1))

    def forward(self, lstm_output):
        attention_scores = torch.matmul(lstm_output, self.attention_weights).squeeze(-1)
        attention_weights = torch.nn.functional.softmax(attention_scores, dim=1)
        weighted_sum = torch.bmm(attention_weights.unsqueeze(1), lstm_output).squeeze(1)
        return weighted_sum

class ComplexRNNModel(nn.Module):
    def __init__(self, input_size, hidden_size, num_layers, num_classes):
        super(ComplexRNNModel, self).__init__()
        self.hidden_size = hidden_size
        self.num_layers = num_layers
        self.lstm = nn.LSTM(input_size, hidden_size, num_layers, batch_first=True, bidirectional=True)
        self.attention = Attention(hidden_size * 2)
        self.fc1 = nn.Linear(hidden_size * 2, hidden_size)
        self.bn = nn.BatchNorm1d(hidden_size)
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(hidden_size, num_classes)

    def forward(self, x):
        h0 = torch.zeros(self.num_layers * 2, x.size(0), self.hidden_size).to(x.device)
        c0 = torch.zeros(self.num_layers * 2, x.size(0), self.hidden_size).to(x.device)
        lstm_out, _ = self.lstm(x, (h0, c0))
        attn_out = self.attention(lstm_out)
        out = self.fc1(attn_out)
        out = self.bn(out)
        out = self.dropout(out)
        out = self.fc2(out)
        return out
```

Figure 4.8: RNN Architecture + Attention mechanism

4.2.7 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN) are a specialized type of neural network primarily used for analyzing visual data. They employ convolutional layers to automatically and adaptively learn spatial hierarchies of features from input images or grids. By applying a series of convolutional filters, CNNs can capture local patterns and features, which are then aggregated through pooling layers to form higher-level representations. Fig. 4.9 shows the general working of CNNs. Fig. 4.10 represents the architecture of CNN model that gave the highest accuracy. This architecture is highly effective for image recognition, object detection, and similar tasks due to its ability to learn and preserve spatial relationships in the data [18].

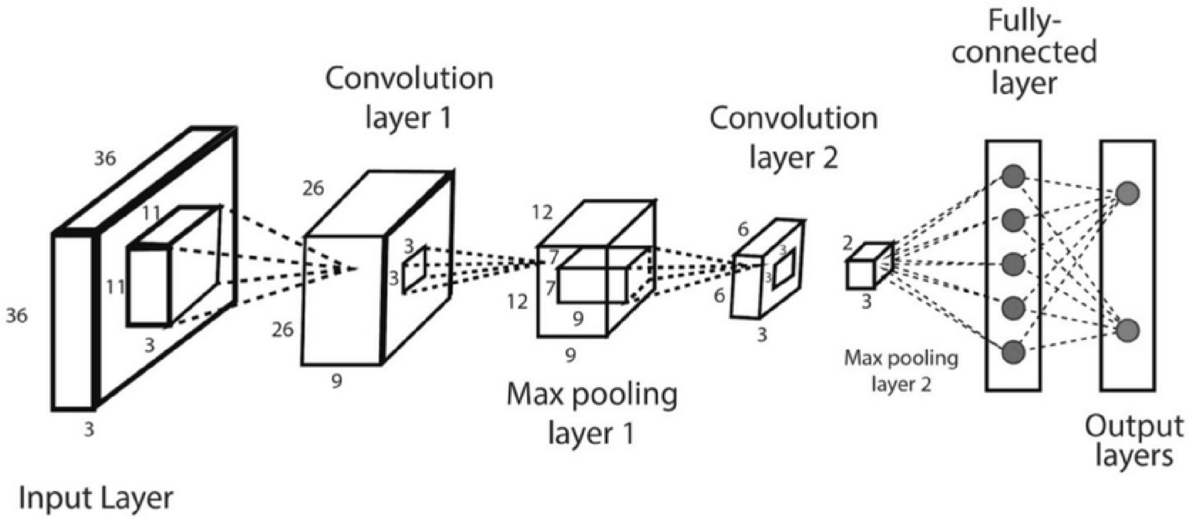


Figure 4.9: Convolutional Neural Networks (CNN)

```python
# Define a more complex CNN model
class ComplexCNNModel(nn.Module):
    def __init__(self):
        super(ComplexCNNModel, self).__init__()
        self.conv1 = nn.Conv1d(in_channels=14, out_channels=32, kernel_size=3, stride=1, padding=1)
        self.bn1 = nn.BatchNorm1d(32)
        self.pool = nn.MaxPool1d(kernel_size=2, stride=2)
        self.conv2 = nn.Conv1d(32, 64, kernel_size=3, stride=1, padding=1)
        self.bn2 = nn.BatchNorm1d(64)
        self.conv3 = nn.Conv1d(64, 128, kernel_size=3, stride=1, padding=1)
        self.bn3 = nn.BatchNorm1d(128)
        self.conv4 = nn.Conv1d(128, 256, kernel_size=3, stride=1, padding=1)
        self.bn4 = nn.BatchNorm1d(256)
        self.fc1 = nn.Linear(256 * 480, 512)  # Adjusted input size
        self.bn5 = nn.BatchNorm1d(512)
        self.fc2 = nn.Linear(512, 128)
        self.bn6 = nn.BatchNorm1d(128)
        self.fc3 = nn.Linear(128, 9)
        self.dropout = nn.Dropout(0.5)  # Increased dropout rate

    def forward(self, x):
        x = self.pool(torch.relu(self.bn1(self.conv1(x))))
        x = self.pool(torch.relu(self.bn2(self.conv2(x))))
        x = self.pool(torch.relu(self.bn3(self.conv3(x))))
        x = self.pool(torch.relu(self.bn4(self.conv4(x))))
        x = x.view(x.size(0), -1)  # Ensure the batch size is preserved
        x = torch.relu(self.bn5(self.fc1(x)))
        x = self.dropout(x)
        x = torch.relu(self.bn6(self.fc2(x)))
        x = self.fc3(x)
        return x
```

Figure 4.10: CNN Architecture being used

5

Results

The contents of this chapter encompass a detailed account of the outcomes and results that were obtained.

5.1 Results and discussion

5.1.1 Performance of Feature Extraction Techniques

- Discrete Wavelet Transform (DWT): The DWT was applied to the EEG signals to extract frequency bands (alpha, beta, gamma, and theta), enabling the isolation of relevant features from different frequency components. When these features were passed to machine learning models, they provided a robust representation of the EEG data, contributing to the classification accuracy.

- Empirical Mode Decomposition (EMD): EMD was utilized to decompose EEG signals into seven Intrinsic Mode Functions (IMFs) for each electrode. This decomposition allowed the extraction of non-linear and non-stationary features, which were particularly useful for capturing intricate patterns within the EEG signals.

- Statistical Features: The extracted statistical features (31 features derived using ANOVA) from both DWT and EMD methods further enriched the feature set, leading to improved model performance. These features encapsulated critical aspects of the EEG signals, such as variability, amplitude, and frequency distributions.

5.1.2 Model Performance

- XGBoost and Random Forest: These ensemble learning models demonstrated strong performance in classifying the nine emotions. The combination of DWT, EMD, and statistical features provided a comprehensive feature set that allowed these models to achieve high accuracy. Among the two, XGBoost showed marginally better performance due to its ability to handle complex interactions within the features and its robust feature selection mechanism.

- Recurrent Neural Networks (RNN): The RNN model, designed to capture temporal dependencies in sequential data, was directly applied to the EEG signals. This model effectively leveraged the time-series nature of the EEG data, yielding strong results in emotion classification, especially in recognizing emotions with distinct temporal patterns. Fig. 5.1 represents the overfitting of RNN model when used with attention mechanism.

- Convolutional Neural Networks (CNN): The CNN model was employed to capture spatial patterns across the electrodes. This model excelled in identifying spatial relationships and correlations between different brain regions, leading to the highest classification accuracy of 90.56% across the nine emotions. The CNN's ability to automatically learn spatial features from the raw EEG data proved crucial in enhancing model performance. Fig.5.2 represents the accuracy of the best CNN model in a random test dataset. Fig. 5.3 represents the mean accuracy of the CNN model in 5-fold cross validation. Fig. 5.4 represents the class-wise accuracy of CNN model in emotion classification. Fig. 5.5 represents the plot for training and validation loss of CNN model along with its validation accuracy.

```
Epoch [7/10], Training Loss: 1.4825
Accuracy on training set: 64.16%
Validation Loss: 2.1728
Accuracy on validation set: 18.29%
Epoch [8/10], Training Loss: 1.4647
Accuracy on training set: 68.07%
Validation Loss: 2.1655
Accuracy on validation set: 15.85%
Epoch [9/10], Training Loss: 1.3514
Accuracy on training set: 71.39%
Validation Loss: 2.1590
Accuracy on validation set: 14.63%
Epoch [10/10], Training Loss: 1.3083
Accuracy on training set: 73.49%
Validation Loss: 2.1520
Accuracy on validation set: 15.85%
Loaded the best model parameters for final evaluation or further training.
```

Figure 5.1: RNN with attention mechanism overfitted the data

```
# Evaluating on random part of dataset just to check
```

```
import torch
from torch.utils.data import DataLoader, random_split
import numpy as np

model.eval()  # Set the model to evaluation mode

# Assuming standardized_data and y_one_hot are already defined and converted to tensors
standardized_data = torch.tensor(standardized_data, dtype=torch.float32).view(414, 14, 7680)
# y_one_hot = torch.tensor(y_one_hot, dtype=torch.float32)
# y_indices = torch.argmax(y_one_hot, dim=1)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Create a dataset
dataset = TensorDataset(standardized_data, y_indices)

# Split the dataset into training and test sets (e.g., 80% train, 20% test)
train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size
train_dataset, test_dataset = random_split(dataset, [train_size, test_size])

# Create a DataLoader for the test dataset
test_loader = DataLoader(test_dataset, batch_size=64, shuffle=True)

# Evaluate the model on the test dataset
correct_predictions = 0
total_predictions = 0
with torch.no_grad():
    for batch_x, batch_y in test_loader:
        batch_x, batch_y = batch_x.to(device), batch_y.to(device)
        outputs = model(batch_x)
        predicted_classes = torch.argmax(outputs, dim=1)
        correct_predictions += (predicted_classes == batch_y).sum().item()
        total_predictions += batch_x.size(0)

test_accuracy = correct_predictions / total_predictions * 100
print(f"Accuracy on test dataset: {test_accuracy:.2f}%")
```

```
Accuracy on test dataset: 93.98%
```

Figure 5.2: Accuracy of best model on random test data

Evaluating the model (Cross fold Validation)

```
[171]: device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
# Function to evaluate the final model
def evaluate_final_model():
    k_folds = 5
    kf = KFold(n_splits=k_folds, shuffle=True)

    val_accuracies = []

    for fold, (train_idx, val_idx) in enumerate(kf.split(dataset)):
        print(f'Fold {fold+1}/{k_folds}')

        val_subset = Subset(dataset, val_idx)
        val_loader = DataLoader(val_subset, batch_size=64, shuffle=False)

        model.eval()

        correct_predictions = 0
        total_predictions = 0
        with torch.no_grad():
            for batch_x, batch_y in val_loader:
                batch_x, batch_y = batch_x.to(device), batch_y.to(device)
                outputs = model(batch_x)
                predicted_classes = torch.argmax(outputs, dim=1)
                correct_predictions += (predicted_classes == batch_y).sum().item()
                total_predictions += batch_x.size(0)

        accuracy = correct_predictions / total_predictions * 100
        val_accuracies.append(accuracy)

    mean_accuracy = np.mean(val_accuracies)
    print(f'Final Model Mean Validation Accuracy: {mean_accuracy:.2f}%')

evaluate_final_model()
```

```
Fold 1/5
Fold 2/5
Fold 3/5
Fold 4/5
Fold 5/5
Final Model Mean Validation Accuracy: 90.58%
```

Figure 5.3: Mean accuracy for classifying emotions using CNN model

```
Fold 1/5
Fold 2/5
Fold 3/5
Fold 4/5
Fold 5/5
Final Model Mean Validation Accuracy for Class amusement: 96.79%
Final Model Mean Validation Accuracy for Class anger: 92.14%
Final Model Mean Validation Accuracy for Class calmness: 88.33%
Final Model Mean Validation Accuracy for Class disgust: 90.91%
Final Model Mean Validation Accuracy for Class excitement: 95.00%
Final Model Mean Validation Accuracy for Class fear: 89.17%
Final Model Mean Validation Accuracy for Class happiness: 90.73%
Final Model Mean Validation Accuracy for Class sadness: 90.95%
Final Model Mean Validation Accuracy for Class surprise: 91.46%
```

Figure 5.4: Mean accuracy class wise emotions using CNN model

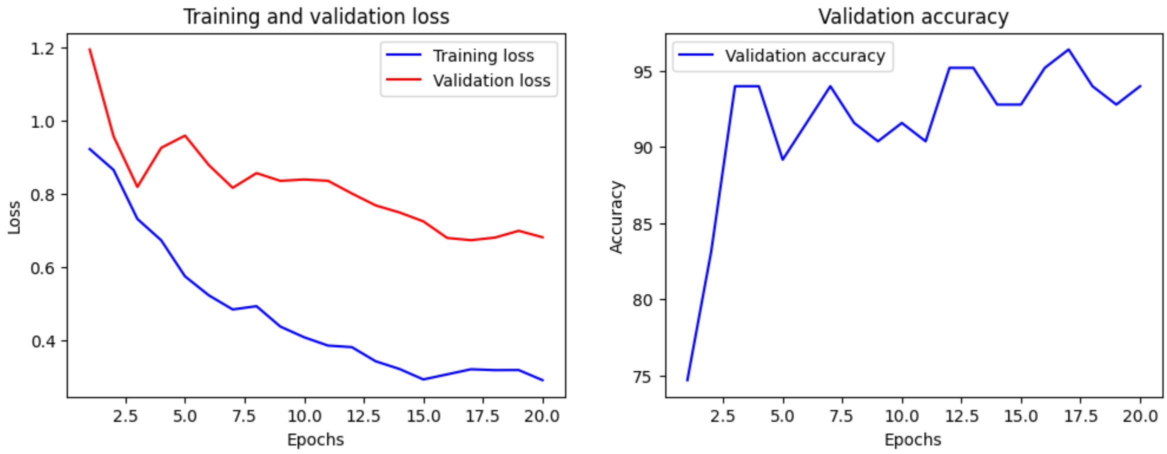


Figure 5.5: Plot for training and validation loss along with its accuracy

6

Conclusions and Future Scope

6.1 Conclusions

In this study, we developed a comprehensive framework for emotion recognition using EEG signals from the DREAMER dataset, employing both traditional machine learning and deep learning models. The combination of feature extraction techniques, including Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD), along with statistical features derived from these methods, provided a robust representation of the EEG data, which was crucial for accurate emotion classification.

Our experiments demonstrated that deep learning models, particularly Convolutional Neural Networks (CNNs), outperformed traditional machine learning models, achieving a high accuracy of 90.56% in classifying nine distinct emotions. This highlights the effectiveness of CNNs in capturing complex spatial and temporal patterns in EEG signals, making them particularly well-suited for emotion recognition tasks.

The results of this study suggest that a hybrid approach, combining both frequency-based and time-domain features, can significantly enhance the performance of emotion recognition systems. The success of CNNs in this context points to the potential for further improvements through the integration of more advanced preprocessing techniques, larger datasets, and possibly the inclusion of multimodal data, such as ECG signals, to provide additional context and improve classification accuracy.

Overall, this work contributes to the growing body of research in affective computing and underscores the potential of EEG-based emotion recognition systems in various applications, ranging from mental health monitoring to human-computer interaction. Future research could explore the application of more sophisticated deep learning architectures and the integration of real-time processing capabilities to further advance the state of the art in emotion recognition.

6.2 Future Scope

Future work will focus on leveraging a Convolutional Fuzzy Neural Network (CFNN) model to enhance the classification of emotions, valence, arousal, and dominance. This approach involves applying Empirical Mode Decomposition (EMD) on the EEG signals already decomposed using Discrete Wavelet Transform (DWT), effectively capturing both time-frequency and intrinsic mode features of the signals before feeding them into the CFNN for more accurate predictions.

Furthermore, the results from this study can be validated using other well-known EEG datasets such as DEAP or SEED, which may offer additional insights and confirm the generalizability of the proposed method. Future research could also explore the integration of additional physiological signals or multi-modal data to improve emotion recognition accuracy.

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