NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF BIOMEDICAL ENGINEERING

ENHANCING THE ACCURACY OF EMOTIONAL RECOGNITION BASED ON EEG SIGNALS BY CONVOLUTION FUZZY NEURAL NETWORK

PhD THESIS

Nasim AHMADZADEH NOBARI AZAR

Supervisor

Assoc. Prof. Dr. Süleyman Aşır

Nicosia

June, 2024

Approval

We certify that we have read the thesis submitted by Nasim Ahmadzadeh Nobari Azar titled "**Enhancing the Accuracy of Emotional Recognition Based on EEG Signals by Convolution Fuzzy Neural Network**" and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of PhD of Educational Sciences.

Examination Committee	Name – Surname	Signature
Head of the Committee:	Prof. Dr. Erbuğ Çelebi	…………………………
Committee Member:	Prof. Dr. Murat Akkaya	…………………………
Committee Member:	Assist. Prof. Dr. Cemal Kavalcıoğlu	……C.K.……………
Committee Member:	Assist. Prof. Dr. Abdullahi U.Ibrahim	…………………………
Supervisor:	Assoc. Prof. Dr. Süleyman Aşır	…………………………

Approved by the Head of the Department

10/06/2024

ASSOC. PROF. DR. SÜLEYMAN AŞIR

Head of Department

Approved by the Institute of Graduate Studies

NEAR EAST UNIVERSITY INSTITUTE OF GRADUATE STUDIES

Prof. Dr. Kemal Hüsnü Can Başer

Head of the Institute

Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

Nasim Ahmadzadeh Nobari Azar
17/06/2024

Acknowledgements

I would like to express my gratitude to all those who have contributed to the successful completion of my thesis. Your support and assistance have been invaluable throughout this journey.

I extend my deepest appreciation to my supervisor, Assoc.Prof.Dr. Süleyman Aşır, for his unwavering support and expertise. His guidance has been instrumental in shaping this thesis.

I would like to express my gratitude to Prof.Dr.Nadire Çavuş and Assoc.Prof.DR.Boran Şekeroğlu for all the guidance, support, and instruction.

My heartfelt thanks go to Mom and Dad; words simply cannot thank you for all that you have done for me. Thank you for your encouragement, patience, positivity, and love from miles away. I would never have been able to achieve my goals without you, and for that, I am grateful.

Special thanks go to my brother for his unwavering encouragement and understanding during this challenging period. Your support has been my source of strength, especially from my brother Vahid, whose unwavering belief in me has kept me motivated.

This achievement would not have been possible without the collective contributions of all those mentioned above. Thank you once again for your support and encouragement.

Nasim Ahmadzadeh Nobari Azar

Abstract

Enhancing the Accuracy of Emotional Recognition Based on EEG Signals by Convolution Fuzzy Neural Network

Ahmadzadeh Nobari Azar, Nasim
PhD, Department of Biomedical Engineering
June, 2024, pages 95

Emotions are a human sensation capable of impacting an individual's quality of life in a positive as well as a negative manner. The capacity to identify various categories of emotions can enable researchers to assess the present condition of patients or the potential of future illnesses. A number of techniques for figuring out emotions from photos, encounter challenges when individuals attempt to conceal their emotions by altering their facial expressions. As a result, there has been an increase in the use of brain signals to accomplish more accurate emotion identification. One of the difficulties scientists encounter when using Electroencephalography (EEG) signals for emotion detection is the dependability of the detection techniques. This challenge prompts researchers to explore alternative classification methods, as the performance of conventional approaches is not dependable. By combining several model features, hybrid deep learning models and other approaches demonstrate a superior ability to analyze complex data and improve performance. Nevertheless, in order to attain the maximum average accuracy, experts emphasize models with less variables. The objective of this research is to enhance the precision of emotion recognition through the utilization of EEG signals, aiming to establish a dependable detection system. The suggested approach combines a Fuzzy Logic system with a 1-D Convolutional Neural Network, forming a hybrid model known as a Convolutional Fuzzy Neural Network (CFNN). This approach utilizes a pair of convolutional layers, a pooling layer, and a fuzzy neural network to extract features. The DEAP dataset, a multimodal dataset comprised of EEG data from 32 participants, is used in this study. The suggested CFNN demonstrated dependable performance for emotion recognition, with average accuracy ratings for valence (pleasantness) and arousal (intensity) of 98.21% and 98.08%, respectively.

Keywords: EEG signal, emotion recognition, deep learning, DEAP dataset, CNN, fuzzy logic**.**

Özet

Evrişim Bulanık Sinir Ağı ile EEG Sinyallerine Dayalı Duygusal Tanıma Doğruluğunun Artırılması

Ahmadzadeh Nobari Azar, Nasim
PhD, Biyomeikal Mühendisliği,
Haziran, 2024, sayfa 95

Duygular, bireyin yaşam kalitesini hem olumlu hem de olumsuz yönde etkileyebilen insani bir duygudur. Çeşitli duygu kategorilerini tanımlama kapasitesi, araştırmacıların hastaların mevcut durumunu veya gelecekteki hastalıkların potansiyelini değerlendirmesine olanak sağlayabilir. Fotoğraflardan duyguları anlamaya yönelik bir dizi teknik, bireyler yüz ifadelerini değiştirerek duygularını gizlemeye çalıştıklarında zorluklarla karşılaşmaktadır. Sonuç olarak, daha doğru duygu tanımlaması gerçekleştirmek için beyin sinyallerinin kullanımında bir artış olmuştur. Duygu tespiti için Elektroensefalografi (EEG) sinyallerini kullanırken bilim adamlarının karşılaştığı zorluklardan biri de tespit tekniklerinin güvenilirliğidir. Bu zorluk, geleneksel yaklaşımların performansının güvenilir olmaması nedeniyle araştırmacıları alternatif sınıflandırma yöntemlerini keşfetmeye sevk etmektedir. Hibrit derin öğrenme modelleri ve diğer yaklaşımlar, çeşitli model özelliklerini birleştirerek karmaşık verileri analiz etme ve performansı artırma konusunda üstün bir yetenek sergiliyor. Bununla birlikte, maksimum ortalama doğruluğu elde etmek için uzmanlar daha az değişkenli modellere ağırlık vermektedir. Bu araştırmanın amacı, güvenilir bir algılama sistemi kurmayı amaçlayan EEG sinyallerini kullanarak duygu tanımanın hassasiyetini arttırmaktır. Önerilen yaklaşım, Bulanık Mantık sistemini 1 Boyutlu Evrişimli Sinir Ağı ile birleştirerek Evrişimli Bulanık Sinir Ağı (CFNN) olarak bilinen hibrit bir model oluşturur. Bu yaklaşım, özellikleri çıkarmak için bir çift evrişimli katman, bir havuzlama katmanı ve bulanık bir sinir ağı kullanır. Bu çalışmada 32 katılımcının EEG verilerinden oluşan multimodal bir veri seti olan DEAP veri seti kullanılmıştır. Önerilen CFNN, sırasıyla %98,21 ve %98,08 değerlik (hoşluk) ve uyarılma (yoğunluk) ortalama doğruluk dereceleriyle duygu tanıma için güvenilir bir performans sergiledi.

Anahtar Kelimeler: EEG sinyali, duygu tanıma, derin öğrenme, DEAP veri seti, CNN, bulanık mantık.

Table of Contents

Approval i

Declaration ii

Acknowledgements iii

Abstract iv

Özet vi

List of Tables xi

List of Figures xii

List of Abbreviations xiii

CHAPTER I

Introduction 1

- Emotion recognition by EEG signals through deep learning ..... **Error! Bookmark not defined.**
- Emotions 2
  - Discrete Emotion Model 4
  - 3D Emotion Model 4
- Explanation of Brain and EEG Patterns 6
  - Operation and Configuration of the Brain 6
- Electroencephalogram (EEG) 7
  - Identifying emotions through EEG measurements 8
  - EEG Preprocessing 9
- Feature Extraction 11
  - Time domain 12
  - Frequency domain 12
  - Time-Frequency Domain 13
- Channel Selection 13
- Classification 14
  - Unsupervised Learning 15

Supervised Learning 15
Deep learning Methods 16
1D convolutional neural networks 20
Fuzzy 22
Fuzzy Neural Networks 23
Statement of the Problem 25
Purpose of the study 25
Significance of the Study 26
Limitations 26
Overview of the thesis 26
CHAPTER II
Literature Review 28
Related Research 28
CHAPTER III
Methodology 35
Method 35
Dataset 35
Proposed Method 37
Pre-processing and Feature Extraction 37
The Proposed Convolutional Fuzzy Neural Network Model 39
Convolutional Neural Network 39
Fuzzy Neural Network 40
CHAPTER IV
Findings and Discussion 47
Measurement of the model 47
Results 48
CHAPTER V
Discussion 55
Discussion 55

CHAPTER VI

Conclusion and Recommendations..59

Conclusion.. 59

Recommendation for future work 60

REFERENCES 61

APPENDICES A...**Error! Bookmark not defined.**

Ethics Committee Approval...**Error! Bookmark not defined.**

APPENDICES B 93

Turnitin Similarity Report.. 93

APPENDICES C 94

Curriculum Vitae.. 94

List of Tables

Table 1. Parameterized FFT explanation 39
Table 2. Comprehensive details regarding the layers of the suggested model 44
Table 3. Evaluation of efficiency of the suggested CFNN with different train/test splits. 49
Table 4. The suggested CFNN's effectiveness with various window sizes. 50
Table 5. Effects (in 75–25%) of the suggested CFNN approach on the DEAP database. 50
Table 6. Results of comparing the suggested CFNN method with state-of-the-art techniques ... 51
Table 7. Performance report for varying train/test splits. 54
Table 8. Comparison between our classification result and the findings of prior research. 57

List of Figures

Figure 1. Illustrates the Valence-Arousal scale introduced by James Russell. 3
Figure 2. The 3D Emotion Model. The 3-letter alphabetical naming system (e.g., NHH) follows these guidelines: the initial letter indicates the valence, either positive (P) or negative (N); the subsequent two letters signify the arousal and dominance, denoting e either high (H) or low (L). (LanZirui, PhD Thesis. P.40) 5
Figure 3. EEG Frequency Bands: Understanding Brain Waves 9
Figure 4. Comparison of EEG Signal Reconstruction After Artifact Removal Using Different Methods... 10
Figure 5. The flowchart of emotion recognition through EEG signal. 35
Figure 6. Descriptive overview of the DEAP dataset. 36
Figure 7. Descriptive overview of the DEAP dataset. 37
Figure 8. Architecture of CFNN model 43
Figure 9. The configuration of the suggested Convolutional Fuzzy Neural Network. 45
Figure 10. The configuration of the suggested Convolutional Fuzzy Neural Network. 46
Figure 11. Graphical visualization of comparison results.. 51
Figure 12. Model test and train graph: (a) Accuracy graph of model in valence; (b) Loss graph of model in valence 52
Figure 13. Model test and train graph: (a) Accuracy graph of model in arousal; (b) Loss graph of model in arousal... 53
Figure 14. Comparisons between our results with the results of previous models 58

List of Abbreviations

EEG: Electroencephalograph

ML: Machine Learning

DL: Deep Learning

NN: Neural Network

CNN: Convolutional Neural Network

1D-CNN: One-dimensional Convolutional Neural Network

DNN: Deep Neural Network

RNN: Recurrent Neural Network

SVM: Support Vector Machine

KNN: K-Nearest Neighbor

Colab: Colaboratory

GHz: Giga hertz

LSTM: Long Short-Term Memory

Bi-LSTM: Long Short-Term Memory

EMG: Electromyography

ECG: Electrocardiography

EOG: Electrooculography

MP: Matching Pursuit

ICA: Independent Component Analysis

EMD: Empirical Mode Decomposition

PSD: Power Spectral Density

DWT: Discrete Wavelet Transform

RMT: Random Matrix Theory

CWT: Continuous Wavelet Transform

RF: Random Forest

DE: Differential Entropy

FaDFR: Fusion After Deep Feature Reduction

CRNN: Attention-based Convolutional Recurrent Neural Network

RNNF: Recurrent Neural Network Fusion

BGWO: Binary Grey Wolf Optimization

ReLU: Rectified Linear Unit

GCNNs: Graph convolutional neural networks

FCM: Fuzzy C-Means

FFT: Fast Fourier Transform

DFT: Discrete Fourier Transform

ANN: Artificial Neural Network

DBN: Deep Belief Network

CDBN: Convolutional Deep Belief Network

1D-FP:1D forward propagation

FNNs: Fuzzy neural networks

ANN: Artificial Neural Networks

CFNN: Convolutional Fuzzy Neural Network

CHAPTER I

Introduction

This chapter introduces a concise overview of emotion and EEG signals, the main objectives of the study, the study significance, hypothesis, and the limitations.

Deep learning-based EEG recording emotion detection

Affective computing has been a comparatively recent area, seeks to equip computer systems having the potential to evaluation, detect, and analyze emotional information provided by people. This endeavor aims to enhance the understanding of human emotions, their triggers, and the design of responsive systems attuned to people's needs, particularly in the realm of human-computer interaction (HCI).

Since emotions are essential to human cognition, that exists to logical decision-making, perception, relationships with others, and intelligence- emotions are vital to people's daily lives (Alarcão & Fonseca, 2019). It is essential for daily social interaction to be able to recognize, understand, and react to other people's feelings. Being able to identify emotions is beneficial for establishing and preserving positive social connections as well as for interacting with a variety of daily activities and social situations (Izard et al., 2001).

To recognize emotions, two main categories of methods are explored: one relies on observable behaviors like facial gestures, speech tone, and bodily movements, while the other utilizes physiological signals recorded by noninvasive sensors to identify feelings with electrical reactions. Emotions are often indicated either in different states, such as the essential feelings proposed by Ekman and Friesen, or within a continuous 4-D space of valence, arousal, dominance, and liking. The latter is often simplified to a 2-D representation of valence and arousal.

There is the close connection between emotion generation and brain cortex activity, with EEG emerging as a valuable tool for detecting brain activity because of its high sensitivity. However, the complexity of EEG data, including channel variety and frequency bands, necessitates advanced tools for analysis. Machine learning and deep learning, particularly 1D convolutional neural networks (CNN), have demonstrated effectiveness in analyzing EEG signals, although traditional ML approaches pose challenges in terms of manual procedures and data loss during preparation.

Deep learning, with its capacity to autonomously grasp intricate features, is harnessed for its success in recognizing various forms of data, including EEG signals. The proposed fused Convolution Fuzzy Neural Network (CFNN) model leverages the strengths of both convolutional neural networks and fuzzy logic. This model is designed to enhance classifying emotions using the DEAP database by combining diverse approaches, ultimately aiming for a deeper and more accurate comprehension of the dataset's emotions.

Emotions

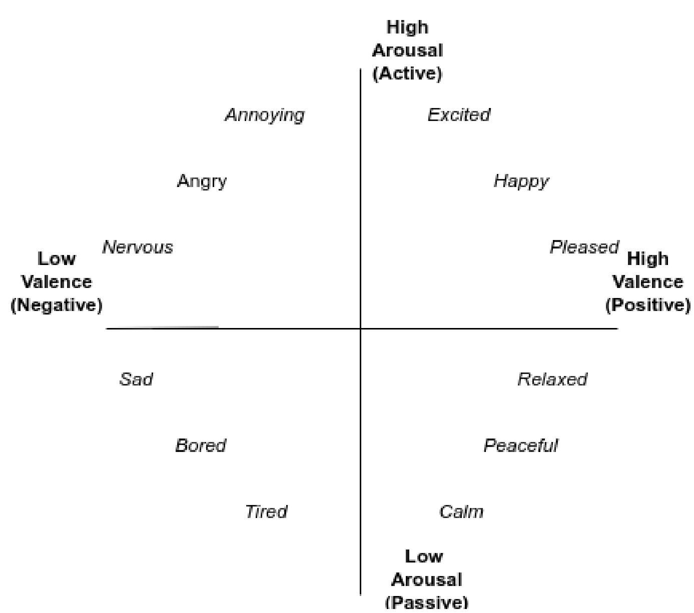
In many aspects of our daily lives, emotions are crucial, influencing choices, educational processes, and how we engage with others. Our choices and behaviors are shaped by the emotional cues we encounter during these experiences. Emotion plays a crucial role in human communication, offering valuable signals that help clarify the messages we convey. Due to technological advancements, everyday routines are increasingly intertwined, involving engagements among humans and between humans and machines. Humans excel at deciphering emotional cues in human-to-human interactions, enabling them to deliver tailored, socially appropriate responses, thereby enhancing the efficiency and smoothness of these interactions (Xu, 2012).

The complexities of human emotion make it a complicated phenomenon that eludes clear explanations. It is usually associated with different aspects of human experience, such as mental states, moods, and emotions, covering both physical and psychological factors, as well as social effects (Ekman & Friesen, 1978). The study of emotions has been an ongoing pursuit since ancient times and currently extends to numerous fields, including philosophy, psychology, neuroscience, social sciences, financial studies, healthcare, historical studies, the arts, and technology for computers (Levensor, 1994). James (James, 1884), known as the "Father of Psychology," proposed one of the initial explanations of emotion. He argues that emotion is a sensation brought on by numerous physical changes and that awareness of these changes in the body produces emotional experiences. Every individual emotion is caused by physical Alterations in the body, like facial expressions, muscular tension, and visceral activity. Lange (Green, 1912) introduced a similar hypothesis in 1885, leading to the subsequent acknowledgment of their collective work as the James-Lange theory, commonly recognized as theory of emotional outer peripheral. The James-Lange hypothesis establishes a basic connection between physiology and emotion (Press, 1927). However, it would rely solely on considering physiological changes in the body's periphery to describe how emotions are produced.

The emotional aspect of humanity is still incredibly intricate, and researchers are always attempting to identify whether every individual emotion exists as an individual and independent entity or if there are correlations and connections among various emotions. Current researchers have suggested numerous categories of essential emotional sets based on their investigations (Healey et al., 2000). Ekman's emotional set includes anger, fear, sorrow, happiness, hate, and surprise, while James's emotional (James, 1884) set comprises rage, fear, sadness, happiness, hate, and surprise (Ekman, Friesen, Sullivan, et al., 1987). Clynes' (Clynes, 1988) emotional range includes rage, hatred, melancholy, happiness, love, romantic sentiments, and a neutral mood state. Izard's (Izard, 2013) emotional range includes anger, fear, sorrow, pleasure, surprise, compassion, disdain, hate, humiliation, and guilt. All of these studies share that the fundamental emotional categories encompass the complete range of human emotions.

Figure 1.

Illustrates the Valence-Arousal scale introduced by James Russell.



Nevertheless, it has been observed that certain emotions, like anger and disgust, might occasionally happen together, showing a link between them. As a result, researchers began using different dimensions to depict emotions depending on their relationships. Lange's two-dimensional mood classification model (Lang et al., 1997), shown in Figure 1.1, is a popular classification approach. The degree of arousal in this paradigm is represented on the ordinate, while the degree of pleasure is expressed on the abscissa, allowing for a progressive shift from low to high arousal and from negative to positive emotions. This two-dimensional framework may be used to classify different emotions, which can then be mapped onto the coordinate system in the appropriate ways.

Emotion models have a vital impact on the investigation of human emotions. In this section, two emotion models will be presented.

Discrete Emotion Model

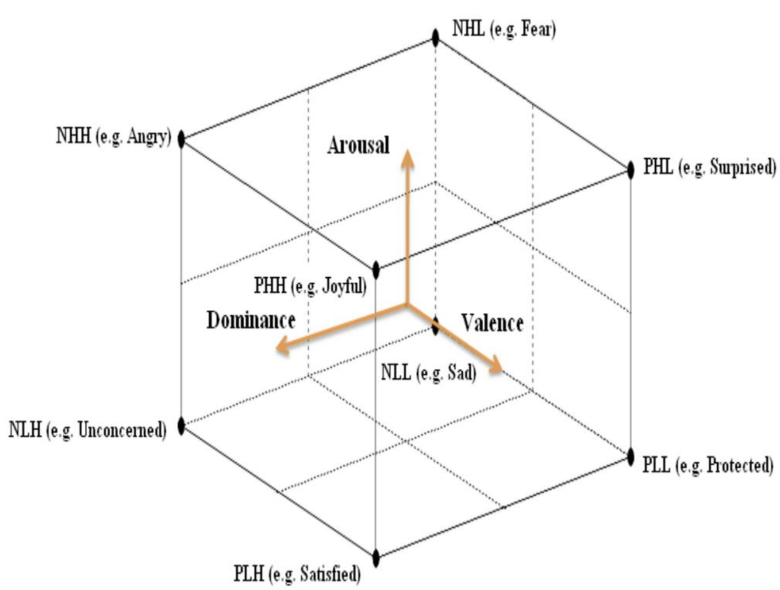
According to the discrete emotion approach, there are a group of basic emotions which can be described, and other emotions can be considered as a combination of these basic feelings. Plutchik's (Plutchik, 2001) discrete emotion model is considered the most influential among the various models in this category. He claimed that emotions in both animals and humans play an important evolutionary role, emphasizing the centrality of eight main feelings such as fear, anger, and joy, sorrow, acceptance, disgust, expectancy, and surprise. According to his hypothesis, these fundamental emotions are evolutionarily primordial and evolved to help animals survive and reproduce (Plutchik, 2001). For instance, when faced with a threat, the animal experiences fear (a basic emotion) and takes action to escape, resulting in a state of safety that enhances its chances of survival. This concept proposes that other emotions are combinations or mixes of the fundamental emotions. For example, contempt could be described as a combination of disgust and anger.

3D Emotion Model

Mehrabian and Russell (Mehrabian, 1996) collaborated in the development of the 3D psychological emotion model. Emotions, according to this concept, can be analyzed and determined using three distinct dimensions: valence, arousal, and dominance. Emotions are assessed on the valence dimension depending on their level of pleasantness, spanning from adverse (unpleasant) to favorable (pleasant). For instance, fear and melancholy are unpleasant emotions with low valence levels. On the other hand, positive feelings such as delight and surprise score high on the valence scale. The arousal dimension assesses the strength of emotion, ranging from low arousal (calm or deactivated) to high arousal (excited or activated). For example, sadness is an emotion with low arousal, indicating low levels of activation, whereas fear is an emotion with high arousal, indicating a high level of activation. The dominance dimension evaluates the extent to which an emotion exerts control or dominance, spanning from diminished dominance (feeling submissive or controlled) to heightened dominance (displaying control or dominance). For example, fear indicates a low level of power as it makes a person more obedient to their circumstances. When someone is angry, they take a dominant attitude, exhibit aggressive tendencies, and have a high level of dominance. Compared to the discrete emotion model, the dimensional emotion model is preferred in emotional investigations.

Figure 2.

The 3D Emotion Model. The 3-letter alphabetical naming system (e.g., NHH) follows these guidelines: the initial letter indicates the valence, either positive (P) or negative (N); the subsequent two letters signify the arousal and dominance, denoting e either high (H) or low (L). (LanZirui, PhD Thesis. P.40)



Source: Seacliff Educational Solutions – Powerful Simplicity (2019).

The dimensional emotion model has been used extensively in several investigations (Lang et al., 1997; Koelstra et al., n.d.). It is indeed possible that there are instances where humans struggle to adequately express or articulate the emotions they are experiencing, or they might express them in a vague manner using adjectives. There may be occasions when we, as humans, find it difficult to communicate or define the feelings we are experiencing, and our descriptions may be overly vague when utilizing adjectives.

Explanation of Brain and EEG Patterns

Operation and Configuration of the Brain

The human brain stands as the most intricate organ, acting as the fundamental center for all neurological systems. It comprises each hemispheres on the left and right, as well as the front the terminus of the third ventricle, which serves as a bridge between the two hemispheres. The cerebral cortex constitutes the outermost layer of the brain. The coordination and communication between the left and right hemispheres are facilitated by the interconnected large fibers that link them together (Frackowiak, 2017). The cerebral hemisphere's surface is not smooth and has a number of sulci. The lateral fissure is a large sulcus located on the upper side of each cerebral hemisphere. These grooves and furrows separate each hemisphere into four lobes. The frontal lobe, the biggest of the four lobes, is situated beyond the central groove and the side cleft and takes up about one-third of the cerebral hemisphere. The temporal lobe sits under the lateral fissure. In contrast, the parietal lobe is situated in the space between the lateral fissure and the central sulcus. Following the parietal and temporal lobes, the occipital lobe is located above the cerebellum (Ketter, 2010). Numerous neurons and several nerve centers may be found in every area of the brain. As a result, each area has a distinct function for controlling, which helps the cerebral cortex to develop a specific functional structure. The following provides concise information on the structure and function of each component:

The frontal lobe, also known as the prefrontal lobe, is of paramount significance to the brain as it fulfills a crucial and vital role. The frontal pole, which is between the frontal pole and the central sulcus, refers to the front most portion of the frontal lobe. The frontal lobe can be divided into three areas: the prefrontal lobe, the frontal motion area, and the primary motor area.

Its functions are mostly connected to cognitive activities including thinking, planning, and emotions (Ketter, 2010).

The parietal lobe, located above the lateral cleft and beneath the central sulcus, mainly handles the interpretation of sensations like pain, touch, taste, and temperature. It is also thought to be involved in managing stress. This region also plays a role in activities including logic and mathematics (Ketter, 2010).

The temporal lobe, which stretches from the bungee (a curving part of the lateral side of the brain) to the occipital lobe, is located below the lateral fissure. The superior section of the temporal lobe manages the interpretation of auditory data. Meanwhile, the frontal section of the temporal lobe contains a mental cortex linked to human memory and emotions (Ketter, 2010).

The occipital lobe is located at the back of the cerebral hemisphere, positioned posterior to the occipital sulcus. Externally, the occipital lobe seems comparatively diminutive, and its sulcus lacks a well-defined boundary. As the main visual cortical center, this lobe is essential for analyzing visual data. It also relates to the impression of movement and words (Ketter, 2010).

The insular lobe is a triangular, island-like structure that is hidden by the frontal, parietal, and temporal lobes deep within the outer sulcus. According to present studies, the insular lobe is significantly linked to emotional regulation and the proper functioning of human internal organs (Ketter, 2010). The Limbic System has a role in memory and the emotion analysis (Ketter, 2010).

Electroencephalogram (EEG)

EEG is an abbreviation for the chronological recording of electrical potentials produced through the natural and regular firing of neurons in the brain. Brain science, mental study, and cognition research indicate that EEG can reveal numerous mental operations and cognition behaviors (Ackermann et al., 2016). As a result, EEG is increasingly employed in the area of emotion identification. Typically, numerous mental states of individuals, including even subtle emotional changes, are directly reflected in EEG data. The application of EEG in this domain is primarily distinguished by the two characteristics following two features (Dietrich & Kanso, 2010).

Because of its low amplitude, EEG is considered a weak signal, making it difficult to collect. Furthermore, throughout the acquisition process, it is vulnerable to interference by physiological electrical signals. Physiological electric signals such as EMG (Electromyography), ECG (Electrocardiography), and EOG (Electrooculography) are examples of the typical noise in EEG signals (Subha et al., 2010). Consequently, the original EEG signals must go through a denoising method that removes such interference.

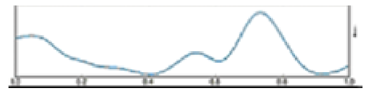
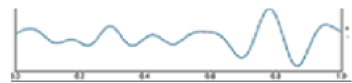
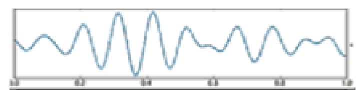
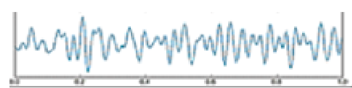
Human feelings, thoughts, and even physiological conditions have an impact on EEG signals, as EEG is a direct representation of brain activity. Because emotional states are relatively independent and brain activity changes in both space and time at every moment, EEG signals exhibit strong nonlinear properties (Garrett et al., 2003).

Identifying emotions through EEG measurements

The primary steps of the procedure include evoking emotions, acquiring EEG signals, preprocessing the EEG data, extracting and choosing features, decreasing features, and performing classification. In EEG recording, the typical approach involves extracting and boosting the signal. As EEG signals are very weak, amplification is necessary to enhance their strength. Following that, the signal must go through an artifact removal procedure using a preprocessing technique. However, the selection of these steps will rely on the particular needs or specifications of each study and may change among different researchers. The following approach is usually used in EEG-based emotion detection studies.

Figure 3.

EEG Frequency Bands: Understanding Brain Waves

Bands	Frequency (Hz)	Amplitude	Cognitive Characteristics	Signal waveform
Delta	0.5-4	20-200	Slow wave activity, commonly occurring in the occipital and temporal lobes, is more frequent in fatigued or anesthetized individuals and does not participate in information processing.	
Theta	4-7	100-150	It belongs to the medium and low amplitude slow wave, appearing during calm relaxation and sleep, expressing the central nervous system's inhibition state and correlating with the working memory load.	
Alpha	8-13	20-100	It is a low-amplitude sync wave, predominantly recorded during a waking quiet state, and is generally associated with brain preparation activity.	
Beta	13-36	5-30	It is a high-frequency, low-amplitude, unsynchronized fast wave indicating the alert state of the brain, visible when emotions are excited or agitated, signifying an excited state of the cerebral cortex.	
Gamma	>36	< 2	Gamma waves play a crucial role in high-level brain functions related to information processing, cognitive activities, attention, and sensory stimulation.	

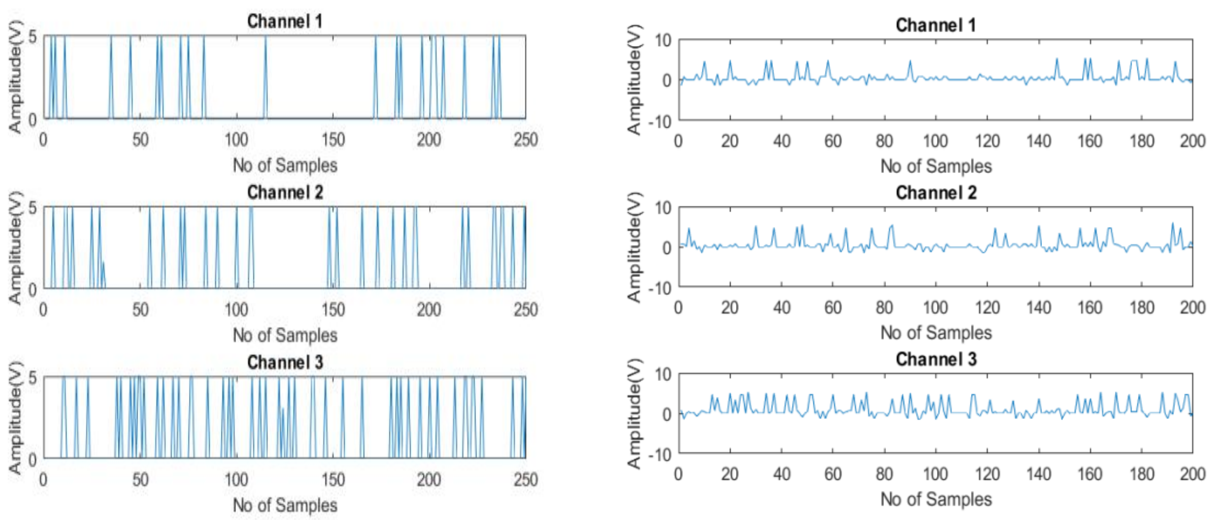
EEG Pre-processing

Because of the faintness of EEG signals, the procedure for acquiring them have a substantial impact on noise signals. EEG preprocessing includes numerous critical processes, including the elimination of line noise, adjusting reference, eliminating poor EEG channels, and removing artifacts (Choi & Kim, 2018). The procedure's main goal is to eliminate disturbances from the captured EEG data. Eye movements (EOG), muscle activity (EMG), heart signals (ECG), frequency disruption, electromagnetic influences, and other irrelevant signals. (Akay &

Daubenspeck, 1999). The Figure 1.4 shows the difference between artifact removal before and after. Multiple methods have been devised to detect and eliminate artifacts associated with EMG and EOG (Wallstrom et al., 2004) (Gratton et al., 1983). As electromagnetic interference and frequency interference usually happen at high frequencies, it may be feasible to employ bandpass filtering or low-pass filtering to remove the disruptive frequency bands and retain just the EEG bands that are significant.

Figure 4.

Comparison of EEG Signal Reconstruction After Artifact Removal Using Different Methods



Source: (Bista & Adhikari, 2017)

Lately artifact elimination approaches include matching pursuit (MP) and independent component analysis (ICA) (Vinther, 2002) (Wcidong Zhou, 2002)(Srivastava et al., 2005). These techniques are utilized to detect and distinguish interference signals, allowing for the distinguishing artifacts from the EEG signal, particularly those that are challenging to remove through filtering. Since it uses mathematical approaches for breaking down the mixed signals into essentially separate components, ICA has emerged to be the most widely used technique for EEG artifact and noise removal. Hence, ICA is capable of separating the signals into EEG and other noise components (Vinther, 2002).

Bartels (Bartels et al., 2010)developed a very successful strategy for artifact removal that combines blind signal separation, ICA, and SVM approaches (Bartels et al., 2010). In particular, the Infomax method of ICA is used for removing EMG artifacts, whereas the Amuse method of blind signal separation is frequently used to remove EOG artifacts. To improve signal pre-processing, Yang et al. (S. Yang & Deravi, 2013) build a model which is hybrid two-stage denoising algorithm with wavelet based noise elimination approach. Recent studies have shown that artifact removal can be achieved rather successfully by combining ICA with additional signal processing technique (Zima et al., 2012) (Subasi & Gursoy, 2010) (Pramudita et al., 2018).Using an intricate neural network with time delays, Rao et al. (Rao & Derakhshani, 2005) compared the effectiveness of MP and ICA in a different study and found that ICA surpassed MP.

Zhou (Weidong Zhou & Gotman, 2009) proposed using ICA and the EEG dipole model to successfully remove certain eye movement artifacts from EEG data. The elimination of ocular and muscular artifacts was proposed by Santillán-Guzmán et al. through the combination of ICA and empirical model decomposition (EMD). In addition, for purpose of further exclude the components identified by ICA that continue to include physiological data, EMD was also utilized (Santillan-Guzman et al., 2018). The EEG preprocessing approach is crucial to EEG-based processing systems. Its primary objective is to eliminate artifacts while leaving them unaffected by the influence of additional physiological signals from humans. Eliminating the noise signals results in more successful and accurate EEG-based research, giving clean and pure EEG data for subsequent processing processes (M. K. Kim et al., 2013).

Feature Extraction

In feature extraction, specific EEG features that are relevant the project's needs are identified and extracted. In EEG-based emotion detection, the process of extracting features is a critical stage that involves selecting only reliable characteristics that correspond to the emotions, ensuring the accuracy of the classification results. Kim provided a concise description of the topic of emotion identification using EEG. The dependable features represent relevant and valuable information modified to match the requirements of a certain task (M. K. Kim et al., 2013). Due to the low amplitude of EEG signals, the procedure for acquiring them have a substantial impact on noise signals. In general, optimum characteristics are critical in obtaining successful and practical performance for identifying feelings or emotional conditions since they significantly influence the distinctive features of EEG-based identification systems (Jenke et al., 2014). Typically, traditional EEG feature extraction involves techniques that frequently employ time-domain, frequency-domain, and time-frequency-domain.

Time domain

The time domain feature pertains to utilizing the EEG signal for the extraction of time-related data and numerical information as features to facilitate subsequent approaches (Romand, 2004). In essence, EEG represents the traditional continuous data that is time-series-based, capturing the most intuitive information that mirrors the fluctuations in human states. Time-domain feature extraction methods mainly include using the initial EEG time series data after removing artifacts, without going through any additional transformation processes as found in other types of feature extraction approaches. Consequently, investigations focusing on time-domain-based EEG research constantly serve as basic and highly productive approaches for EEG processing methods.

Frequency domain

The process of extracting critical frequency features as EEG features involves turning the primary EEG signal from its based on time domain to the frequency-based. The frequently employed EEG frequency ranges (delta: 1-4 Hz, theta: 4 Hz, alpha: 8 Hz, beta: 13 Hz, and gamma: 36 Hz) correspond to diverse physiological and psychological functions in humans. The distinct EEG frequency bands indicate different roles and operations of the human brain, either individually or through their cooperation. These functions include areas for instance emotions, recollection, determination, facilitation, and more (Klimesch, 1999). In frequency-based EEG research, the initial stage involves converting time-series data into frequency domain, which can be achieved using various methods like Fast Fourier Transform (FFT) and Discrete Fourier Transform (Wang et al., 2011) (Aljalal et al., 2018).

Variables such as band power, power spectrum, and power density spectrum are often used in frequency domain. Many EEG research use features determined by frequency, particularly in the area of emotion identification. Zouridakis suggested a method in which the raw EEG data undergoes bandpass filtering subsequently divided to five frequency bands. In order to recognize emotions, the matching band power for each of five bands is computed and utilized as a feature

(Zouridakis et al., 2010). Aftanas proposed a technique wherein the raw EEG signal is transformed to theta, alpha, and beta bands using FFT. Subsequently, the Power Spectral Density (PSD) of every electrode is determined and utilized as an emotion detection feature (Aftanas & Golocheikine, 2002). Many researchers focus on investigating in each of the five distinctive frequency bands observed in the EEG data and human emotions. Li et al. (Mu Li & Member, 2009) specifically conducted on the connection of the EEG gamma band and two distinct feelings, namely happiness and sadness. Jauovec et al. (Jaušovec et al., 2001) suggested a concept of Emotional intelligence in humans in relation to the theta and alpha EEG frequency bands. However, in contrast, Zhang et al. conducted a study comparing the representation using identical frequency-based features and classification techniques to assess the levels of the five frequency bands individually.

Time-Frequency Domain

When dealing with non-stationary signals, time-frequency methods can provide useful data examining the dynamic variations (Jenke et al., 2014). Since the nature of EEG data is unstable, concentrating just on time- or frequency-domain characteristic features is insufficient. As a result, numerous EEG time-frequency domain investigations have emerged in recent years to identify features that can comprehensively represent properties from both time-based and frequency-based. Furthermore, the primary focus of the time-frequency domain is on recording dynamic changes in time-series data, which correlates to a key aspect of emotion studies. Since the physiological interpretation of human emotion is time-dependent, once a certain emotion is experienced, it typically continues for a certain period of time before gradually returning to a state of calm (Ekman, Friesen, O’Sullivan, et al., 1987).

Channel Selection

Essentially, EEG signals encompass a distribution across the head. Various locations of these EEG signals correspond to distinct brain functional zones, meaning that not all EEG signal channels contribute equally to the formation of emotions (Alotaiby et al., 2015). In the brain, specific regions are correlated with emotions, causing channels from different regions to be unrelated to classifying of emotion. Channel selection, like feature selection, can be categorized into two ways: filter and wrapper techniques. Furthermore, in specific tasks, the filter and wrapper approaches can be combined to enhance the selection process (Gnana, 2016).

Karim et al. (Ansari-Asl et al., 2007) suggested synchronizing with probability as a technique for selecting channel method to identify relevant channels and accomplish feature reduction. Zheng et al. (W. L. Zheng & Lu, 2015) applied a deep belief network and the four selected channels to classify emotions, and they demonstrated that the performance of the chosen data was much better than that of the whole data when using the identical experimental setup. Zhang et al. (Jianhai Zhang et al., 2016) introduced a channel selection technique due to the relief algorithm to identify the most relevant channels for identifying four emotional states (joy, fear, sorrow, and relaxation). They chose 19 channels from the 32 that were accessible in order to recognize emotions accurately. Another crucial component of channel selection involves taking into consideration what corresponds to with electrodes on both sides of the brain. These symmetrical electrodes signify many functional space of the brain, each in responsible for controlling various representations of human behavior. According to Rizon et al. (Transactions et al., 2016), one way to select a channel is to utilize the ratio asymmetry of symmetrical electrodes. The difference in the ratio between symmetrical channels on every brain side was utilized as an indication to depict the functional area of the brain and to identify channels related to recognizing emotions. Out of the 63 channels available, they selected 28 pairs for five emotions (disgust, happy, surprise, sad, and fear). The findings showed significant efficiency improvements when using these pairs of channels.

Classification

EEG classification refers to the process of using existing EEG features to make observations and infer the specific emotional state that an individual is experiencing. Typically, features are input into classifiers to train the rules for identifying the corresponding emotions with a high level of accuracy using different algorithms. Emotion recognition through EEG includes two main tasks. How to identify the EEG patterns corresponding to different emotional states using EEG features? How to categorize untrained feature samples based on their associated EEG patterns? The recognition of emotion state could be categorized into two main methods: unsupervised learning and supervised learning algorithms (M. K. Kim et al., 2013).

Unsupervised Learning

Unsupervised learning includes training on data without identifying category information with the goal of bringing similar characteristic samples closer while simultaneously moving away from different characteristic patterns. As a result, this approach achieves classification by grouping similar samples together and separating different samples from one another. In the domain of EEG-based emotion research, unsupervised learning is frequently employed (Gath & Geva, 1989). Because there are no predetermined rules for identifying emotions through experimentation, this is mostly because human emotions are complicated and autonomous. Obtaining reliable EEG data labeled with emotions in particular is made more difficult by the lack of standards for classifying emotional states based on physiological data (Mahajan & Morshed, 2015). Nevertheless, unsupervised learning presents a potential solution that allows the system to self-learn and recognize various categories without explicit labeling.

Supervised Learning

Supervised learning requires labeled sample categories and includes continually adjusting the model's parameters depending on the provided category information. Subsequently, the test samples are classified using the trained model. In contrast to unsupervised learning, supervised learning focuses largely on the labels applied to each category, which enable the model to generate accurate predictions. In general, there are two labeling approaches that are typically employed on emotion detecting based on EEG. First, using the arousal-valence two-dimensional model—which is widely used in the field of psychology—the emotions can be classified and identified (Ekman, Friesen, O'Sullivan, et al., 1987). These two elements separately determine diverse emotional states depending on varied combinations of arousal and valence levels (Koelstra et al., n.d.) (Sourina & Liu, 2011) (J. Liu et al., 2016). An alternative method of identifying emotions is to determine each participant's individual emotional state at the time of the experiment's application of stimuli, and utilize that state as the label. Some auxiliary measures, such as facial expressions, physical movements, heart rhythm, heartbeat, and the emotional qualities of the stimuli utilized in the experiment, can be used to reliably categorize emotions for participants.

Deep learning Methods

In order to obtain data at different levels of abstraction, deep learning is a subfield of machine learning that uses mathematical and algorithmic frameworks with many processing layers. These processing layers often include pooling, activation functions for non-linearity, and linear transformations. Each layer extracts progressively more abstract features from the data. In general, the entire model is called a neural network (NN). A basic NN, without intermediary layers, was suggested by Rosenblatt (1957). Subsequently, in the 1970s and 1980s, Hinton's research team suggested deeper, more intricate networks like the one with multiple layers (MLP), as well as more sophisticated network topologies (Rumelhart & Hinton, 2019). Bengio (Bengio, 2009) is one of the researchers who made noteworthy achievements in promoting deep networks and helped to develop the field (Goodfellow et al., 2020). Lecun et al. (2015) give a concise overview and position on the topic of deep learning, emphasizing two of its most remarkable features: the depth learning network structure's suppleness in constructing and the gradient descent time's simplicity.

As an example, convolutional neural networks (CNN) were suggested towards the end of the 1980s to achieve transformation consistency in pictures. To represent time series data and record long-term dependency between time intervals, recurrent neural networks (RNN) were suggested and applied in speech detection (Graves et al., 2014) as well as in natural language processing (Devlin et al., 2019). However, the latest research suggests that time-based convolutional networks (Shikano & Lang, 1989) could achieve similar or even superior performance (Bai et al., 2018).

A popular classification method that mimics the structure of the valid neural network in the human brain through mathematics is called an artificial neural network, or ANN. The multilayer perceptron is a popular NN model that utilizes sample categorization data provides a guide to iteratively adjust parameter weights from the middle layer to the output layer up to until specific criteria are met. Once trained, this perceptron is used to classify samples (Ruck et al., 1990). Estepp et al. (Estepp et al., 2011) utilized ANN for classifying unstable cognition levels and achieved remarkable results. Zheng et al. (W. Zheng et al., 2015) introduced the deep belief network (DBN) as a method to extract EEG features for emotion detection. Ren and Wu. (2014) suggested using the convolutional deep belief network (CDBN) as a method for extracting feature, as they assume it possessed strong capabilities in feature learning and understanding. Due to advancements in deep neural network modules, notable accomplishments have been achieved in various domains, including image processing (Lecun et al., 2015) and sequential data processing (Hochreiter & Schmidhuber, 1997). Numerous studies show that deep learning algorithms have made great progress in EEG-based recognition research and are competitive with other approaches.

Three categories exist under the idea of applying deep learning techniques: sequence-based analysis, image-focused analysis, and image-and sequence-based processing. Yanagimoto & Sugimoto (2016) suggested using a supervised pre-trained Convolutional Neural Network (CNN) for emotion detection utilizing EEG frequency domain features, and they obtained outstanding results. Tripathi (2012) suggested investigating the most successful configurations of a basic DNN and a CNN for emotion detection. Song et al. (Song et al., 2020) introduced the dynamic graph CNN to reach emotion detection. This approach involved constructing a dynamic graph model to represent the EEG with multiple channels characteristics and record emotional state using a neural network. The outcomes demonstrated a substantial improvement when applied to two publicly available datasets for EEG based emotion detection. Moon et al. (Moon, Seong-Eun, Jang Soobeom, 2018) suggested that CNN possesses the ability to incorporate spatial information through filters in two dimensions applied in the convolutional layers. Consequently, they utilized EEG characteristics of connection as input for a CNN and successfully achieved emotion classifying outcomes. Mei et al. (Satuluri et al., 2022) recommended using CNN to extract features from the correlation matrices of multi-channel EEG electrodes that successfully recognized emotions. Alhagry et al. (Alhagry et al., 2017) put forth a proposal for sequential processing in emotion recognition, wherein they employed Long Short-Term Memory (LSTM) as the method for processing time series data. The EEG data was divided into sequences, which were subsequently fed into LSTM. Their approach yielded substantial improvements compared to state-of-the-art methods. Nakisa et al. (Nakisa et al., 2018) introduced a similar method for EEG emotion detection utilizing LSTM. Within their approach, the input to LSTM was the differential entropy of EEG recordings. They conducted a comparison with using alternative hyperparameter methods for optimizing and attained superior results, outperforming the alternatives.

CNN have completely transformed the environment of image processing and artificial intelligence form the time of introduction (Lecun et al., 2015). At first, they employed for handling images and videos within the domain of computer vision. However, through subsequent research, they are utilized in various fields, such as natural language and electrical brain waves. These types of networks are particularly effective at collecting locally correlated spatial features in the information.

Convolutional layers, which make use of the convolution process, are the main component of CNNs. In order to extract feature maps, the following procedure involves a number of filters or kernels across the information that was provided. A hyperparameter called the stride determines the size of the output feature map. The first step in the feature extraction process of a CNN is to extract basic feature from the input data, which might include elements like edges or lines in an image. Following that, more advanced features are obtained as we delve deeper into the network, including faces, things, patterns and colors, and surfaces. The feature maps are employed to reduce the resolution by using pooling layers and algorithms like maximum or average pooling. Backpropagation is typically used to compute the loss and gradients in order to modify the weights for the filters and kernels. Additionally, a supervised technique is employed to train these networks.

Typical CNN structure involve sequences of stacked convolutional layers, which are subsequently followed by layers for normalization and pooling. However, if implemented in a deeper network, numerous blocks would need to be stacked.

The CNN comprises multi phases neural network that consisting of filtering and classification steps. The filtering phase is employed to extract features from input signals, while the classification process categorizes these extracted features. The network variables for both phases are acquired through simultaneous training. The filtering phase comprises three fundamental elements: convolutional layer, a pooling layer, and an activation layer, whereas the classification phase typically comprises of the fully connected layer. The four layers structure can be elucidated as follows:

***Convolutional layer*:** The convolutional layer applies convolution operations to localized area of the input signal using convolutional kernels to produce related features. The key characteristic of the convolutional layer is weight sharing, where a consistent convolutional kernel moves across the input with a defined stride. The relevant coefficient of the convolution kernel with the neuron within the rolling area of the convolution process are multiplied to calculate the initial logits value. Once the convolution kernel is shifted incrementally, and the preceding operation is reiterated until the kernel has covered all sections of the input signal.

Activation layer**:** Each convolution output's logits value is transformed non-linearly by the activation function. The role of the activation function is to turn the initial linear and inseparable multidimensional feature into a different space where its linear separability is improved. The sigmoid function, hyperbolic tangent function Tanh, and modified linear unit rectified linear unit (RELU) are among the regularly employed activation functions in neural networks.

Pooling layer**:** With the main objective of lowering the neural network parameters, the pooling layer is used to reduce the size. Max and average pooling are two types of pooling functions. Mean pooling calculates the output value by taking the average of neurons within the receptive field, whereas maximum pooling determines the output value by selecting the highest value within the receptive field.

Fully connected layer: The fully connected layer is responsible for categorizing the features that have been extracted during the filtering phases. In particular, the last pooling layer's output is initially transformed into a one-dimensional feature vector, which then serves as the input for the fully connected layer. The fully connected layer is constructed through complete connections between the input and output.

CNN

Even though the initial CNN was suggested about three decades ago, current CNN designs continue to have elements in common with the original, including the utilization of convolutional and pooling layers. Additionally, the widely used training approach known as back propagation has remained common since the 1990s. Firstly, the widespread use and variety of deep CNNs can be attributed to the subsequent benefits:

CNN combines the processes of feature extraction and classification attributes into a unified learning framework, enabling direct extraction of features from the unprocessed input data through the training stage. Due to the sparse connections and weight sharing among CNN neurons, CNNs demonstrate superior computational efficiency when handling huge inputs compared to conventional fully connected multi-layer perceptron networks. CNNs exhibit resilience against minor alternations in input data, resizes, distortions, and skewing. Moreover, varying input dimensions can be supported by CNNs. The input, output, and scalar weights of each neuron in a typical MLP are composed. In contrast, in a CNN, owing to the two-dimensional nature of images, every neuron comprises two-dimensional weight planes referred to as kernels, along with inputs and outputs called feature maps.

1D convolutional neural networks

The standard deep CNNs are constructed specifically to process 2D data, including photos and movies. On the other hand, recently, one-dimensional Convolutional Neural Networks (1D CNNs) have been constructed as an improved form of 2D CNNs. A 1D CNN has substantially less computational complexity than a 2D CNN. As 1D CNN is utilized in the compact configuration with a smaller number of hidden CNN layers and fewer parameters. So, shallow architectural networks are certainly simpler to train and execute. However, training a compact 1D CNN with only a few hidden layers is both possible and rather quick when using any CPU implementation. Because of their low processing demands, compact 1D CNNs are well-suited for real-time and cost-effective applications, especially on mobile or portable devices. 1D forward propagation (1D-FP) is stated as follows in each CNN-layer (Equation (1)):

$$x_k^l = b_k^l + \sum_{i=1}^{N_{l-1}} conv1D(w_{ik}^{l-1}, s_i^{l-1}) \quad (1)$$

Where x_k^l is represents the input, b_k^l represents the bias of the k^{th} neuron at layer *l*, s_i^{l-1} is the output of the i^{th} neuron at layer *l-1*, w_{ik}^{l-1} represents the kernel from the i^{th}neurons at layer *l-1* to the k^{th} neurons at layer *l*. $conv1D(.,.)$,'in-valid'1D convolution is performed without zero-padding. As a result, the size of the output array,y_k^l is more than the size of the input array,x_k^l. If the input x_k^l is passed via the activation function, *f*, the intermediary output, y_k^l can be represented as follows (Equation(2):

$$y_k^l = f(x_k^l) and\ s_k^l = y_k^l \downarrow ss \quad (2)$$

s_k^l represents the output of the k^{th}neuron in layer, l and $\downarrow ss$ denote the down-sampling process using a scalar factor, and ss. A concise summary of the back-propagation (BP) method is as follows. The process of error BP initiates from the output MLP layer. Consider the input layer as *l=1* and *l=L* as the output layer, N_L as the amount of classes in the dataset, and its target and output vectors, given an input vector p, t^p and $[y_1^L, \ldots, y_{NL}^L]'$. As a result, in the input p's output layer, the mean-squared error (MSE), Ep, is stated as follows (Equation (3)):

$$E_p = MSE\ (t^p\ , [y_1^L, \ldots, y_{NL}^L]') = \sum_{i=1}^{N_L} (y_i^L - t_i^p)^2 \tag{3}$$

To determine E_p's derivative by each network parameter, the delta error, $\Delta_k^l = \frac{\partial E}{\partial x_k^l}$ needs to be calculated. To be more precise, when updating the bias of that particular neuron and adjusting the weights of the neurons in the preceding layer, you can apply the chain-rule of derivatives in the following manner (Equation (4)):

$$\frac{\partial E}{\partial w_{ik}^{l-1}} = \Delta_k^l\ y_i^{l-1}\ and\ \frac{\partial E}{\partial b_k^l} = \Delta_k^l \tag{4}$$

Consequently, the normal (scalar) BP can be easily carried out as it is applied from the first MLP layer to the last CNN layer (Equation (5)).

$$\frac{\partial E}{\partial s_k^l} = \Delta s_k^l = \sum_{i=1}^{N_{l+1}} \frac{\partial E}{\partial x_i^{l+1}} \frac{\partial x_i^{l+1}}{\partial s_k^l} = \sum_{i=1}^{N_{l+1}} \Delta_k^{l+1}\ w_{ki}^l \tag{5}$$

After the initial back-propagation is carried out from the subsequent layer, *l+1*, to the present layer, *l*, the BP can subsequently be applied to the CNN layer's input delta, Δ_k^l. Consider the up-sampled map at zeroth order as: $us_k^l = up\ (s_k^l)$, In that case, the error delta can be represented as follows (Equation (6)):

$$\Delta_k^l = \frac{\partial E}{\partial y_k^l} \frac{\partial y_k^l}{\partial x_k^l} = \frac{\partial E}{\partial us_k^l} \frac{\partial us_k^l}{\partial y_k^l}\ f\ \acute{x}_k^l = up\ (\Delta s_k^l) \beta \acute{f}\ (x_k^l) \tag{6}$$

Whereas $\beta = (ss)^{-1}$. The delta error's BP is subsequently calculated ($\Delta s_k^l \leftarrow \Delta_i^{l+1}$) can be stated as (Equation (7)):

$$\Delta s_k^l = \sum_{i=1}^{N_{l+1}} conv1Dz(\Delta_i^{l+1}, rev\ (w_{ki}^l)) \tag{7}$$

As $rev(.)$ is utilized for reversing the array, and $conv1Dz(.,.)$ is employed to produce full one-dimensional convolution with zero padding. Following is an example of how to express the weight and bias sensitivities (Equation (8)):

$$\frac{\partial E}{\partial w_{ik}^{l}} = conv1D\left(s_k^l, \Delta_i^{l+1}\right) and\ \frac{\partial E}{\partial b_k^l} = \sum_n \Delta_i^l(n) \quad (8)$$

The learning factor may be used to update biases and weights by computing the weight and bias sensitivities, ε as (Equation (9)):

$$w_{ik}^{l-1}(t+1) = w_{ik}^{l-1}(t) - \varepsilon \frac{\partial E}{\partial w_{ik}^{l-1}}\ and\ b_k^l(t+1) = b_k^l(t) - \varepsilon \frac{\partial E}{\partial b_k^l} \quad (9)$$

Fuzzy

Lotfi A. Zadeh introduced the notion of soft computing in 1981. He described soft computing as a multidisciplinary system that combines various domains, including fuzzy logic, neural networks, evolutionary computation, machine learning, and probabilistic reasoning. Soft computing emerges from the techniques designed for modeling and offers solutions real-world challenges that could be exceedingly complex for conventional methods to precisely represent.

Soft Computing encompasses multiple computational techniques. It is a cooperation where each participant provides a unique approach to solving issues related to their specific fields. From this point of view, the main approaches within soft computing complement each other rather than compete (Zadeh, 1994). Additionally, soft computing can be seen as a key element of the developing area of conceptual intelligence. The two significant techniques include fuzzy logic and neural networks.

Fuzzy logic, initially introduced by Zadeh in 1965, provides a generic approach to dealing with ambiguity and expressing the subjective understanding that is prevalent in the natural world. It employs logical operators to gather the information to approximate causes. Fuzzy logic encodes a form of information within digital computers using fuzzy sets, whereas a fuzzy inference system (FIS) is a computational framework founded on the principles of fuzzy sets, fuzzy if-then, and fuzzy reasoning. Fuzzy implication and the rule of interference composition are two principals that connect to a set of fundamental linguistic concepts that form the base of FIS. It has been effectively used in several real-world contexts, including engineering, economics, and more. Fuzzy logic provides a few benefits over other approaches:

1. By using fuzzy functions for membership, fuzzy logic-based reasoning can be used to represent complicated and nonlinear systems.

2. Fuzzy systems are comprehensible and assessable, and they can be constructed based on expertise or prior findings from experiments.

3. Fuzzy systems can deal with data that is not certain because of its uncertain nature.

Fuzzy Neural Networks

Customized systems designed for individual datasets have become critical for efficiently integrating and managing massive volumes of data. Simultaneously, intelligent systems with high levels of efficiency in dealing with data-related issues include models of artificial neural networks. However, due to the difficulties in understanding their outputs as a result of their complicated internal workings, their black-box structure restricts their widespread adoption. Fuzzy systems rely on training data resources to detect pertinent features, enabling the development of expert systems, particularly rule-based ones.

Fuzzy neural networks (FNNs), which merge the benefits of artificial neural network approaches with fuzzy systems, are neural networks that contain fuzzy neurons (Chin-Teng Lin et al., 1996). The harmonic combination of various methodologies enables the models to solve problems of diverse complexities and extract information for better decision-making. Fuzzy neurons are created by utilizing data through a fuzzification process. Fuzzy neurons with logical capabilities can carry out operations within hidden layers, while the model's output is handled by the artificial neural network. Fuzzy neural network have the capacity to generate fuzzy rules, which can aid in the development of expert systems (Pedrycz & Gomide, 2007). Hence, a fuzzy neural network comprises fuzzy neurons as its fundamental building blocks.

Developing a neuro-fuzzy network model includes combining fuzzy rule structures with artificial neural network training definitions (such as recursive or incremental approaches). They have a close connection to the environment they investigate, adjusting to its time-varying nature and processing non-stationary flow data. These models differ significantly from traditional neural network models in that they may merge the advantages of fuzzy inference systems with the training capability of ANN. Hence, the process of extracting knowledge may be valuable for other applications, meanwhile the model itself possesses enhamced and effective problem-solving capabilities. The input and output layers are the primary architectural components of fuzzy neural networks. The structure of hidden layers in these models is dependent on the level of capability in fuzzy inference systems or collections generated by neural networks.

The structure of FNNs can differ based on the model's complexity or the specific tasks they are designed to handle. These networks consist of distinct layers, each tasked with specific functions like fuzzification, combining rules, and trimming. The interaction among these layers adheres to the structure commonly seen in neural networks, and the training models are also influenced by ANN. The depiction of the structure in fuzzy neural networks stimulates the development of novel models in the literature. The most prevalent arrangement for a Feed-Forward Neural Network (FNN) architecture is for each layer of the model to have neurons with different levels of fuzziness. This setup facilitates the unidirectional transmission of signals throughout the entire network. Typically, neurons within a layer communicate only with neurons in the preceding and subsequent layers. Every layer could possess a distinct quantity and number of these fuzzy neurons, depending on the model. No matter how many layers a model has, the fuzzification and defuzzification process is usually performed by one of them.

The concept of architecture in FNN promotes the advancement of novel models in the field of study. The most typical architectural arrangement for FNN is called feed-forward, where every layer of the model consists of fuzzy neurons, enabling a single-direction signal to progress through the entire network. Usually, just the neurons in the front and backward layers are able to communicate with those in a layer. The behavior and function of the fuzzy neurons, and the number of them in each layer, can differ from one model to another. Additionally, the total amount of layers varies. There are three layers in the majority of FNN models. Additionally, there exists a diverse array of models featuring four and five layers. The features such as layer aggregation or layer pruning of fuzzy neurons are generally tied to a number more than the three standard layers. Researchers can design models that suit their requirements due to the flexibility. The researcher first decides how many layers he wants to use, which type of neurons he is going to use and which conditioning method seems to work the best. The last layer, for generating the final outputs, is placed as the very last layer in the model. Although anytime confuse up layers with the number of layers a model comprises, fuzzification and defuzzification get usually dealt by using a layer even if the model comprises multiple layers. This indicates that the provided data will be useful for the model to process and produce accurate results.

Statement of the Problem

To enable computers to comprehend and identify emotions, it's essential to gain the origins of physiology and emotions in human body. Emotions are often represented by spoken language, for example, by using familiar words, or through non-verbal means, including variations in vocal intonation, expressions on the face, and physiological changes within human nervous system. Since expressions in the face and vocal tones can be manipulated or may not always reflect accurate an emotion, they are unreliable predicators of one's emotional state. The physiological signals are accurate to a greater extent since users cannot manipulate or influence them.

The measurement of brain electrical activity using EEG is now widely recognized as standard technique. The electrodes are affixed to the participant's scalp in the non-invasive method of data collection. Since EEG signals are naturally low in intensity and responsive to interference from various internal and external sources, potential noise originating from the body of an individual or electrodes. The artifacts pertain to the noises or unwanted disturbances. During EEG recording, electrodes can inadvertently capture undesirable electrical signals like the electromyogram (EMG) from neck muscles and eye blinks.

The proposed Fuzzy-CNN model can deal with unwanted noise in the dataset.

Purpose of the study

The aim of this study was to determine:

1. We proposed a CFNN-based model for recognizing emotions from the EEG signals. The proposed model combines the advantages of both CNN and fuzzy logic in extracting beneficial features from dataset.

2. The two model versions are compared with different window sizes, one with a CNN and fuzzy layer and other without fuzzy logic, which confirms the superior performance of our approach.
3. The efficiency of the model was evaluated by applying the DEAP dataset, based on accuracy and loss metrics.

Significance of the Study

In this study, the EEG signals for the first time employ as an input to the proposed model. The model presents an approach that uses layers of fuzzification and defuzzification transform flattened features into fuzzy numbers, which are subsequently converted to crisp value. This innovative approach not only boosts classification accuracy through the use of fuzzy neural networks but also acknowledges the potential richness of information within fuzzy sets, leading to enhanced accuracy. The model's proficiency in handling noise disruption further underscores its improved capabilities in the realms of detection and classification. Also, the research underscores the importance of employing Fast Fourier Transform (FFT) in order to extract features, elucidating how it enriches the classification model by extracting pertinent frequency-domain information from input signals, thereby augmenting its discriminative power.

Limitations

Studies on emotional recognition face a variety of difficulties, which are related to data collection methods, instruments, objectives, etc. The utilization of other datasets to validate the suggested methodologies is impeded by these variances, which result in diverse and unique datasets. The suggested model has not been applied to various datasets with varying. Features, and further research is needed to generalize the outcomes in real-time applications.

Overview of the thesis

The study aims to pioneer a novel approach by using signals as inputs for CFNN, enhancing emotion classification accuracy through the application of fuzzy neural networks, proficiently managing noise disruption, exploring the richness of information in fuzzy sets, and highlighting the impact of Fast Fourier Transform (FFT) in improving the discriminative power of the classification model. A summary of the chapter’s contents is provided below:

- Chapter I: It gives a summary of advancements in enhancing the precision of emotion recognition using CFNN models applied to EEG signals. The statement outlines the research problem, the study's objective, the significance of the research, and provides a general overview.
- Chapter II: Discuss the relevant studies on emotion detection based on EEG signals in machine learning and deep learning. The theatrical framework and literature review is conducted.
- Chapter III: Include the research methodology, provide details about the dataset, outline the pre-processing steps, the feature extraction process, the classification approach, and the theoretical explanation of the employed model.
- Chapter IV: Presents an in-depth exploration of the design and implementation of the proposed modeling approaches.
- Chapter V: Presents a comprehensive conclusion, offers recommendations based on the findings, and puts forth proposals for future research endeavors, extending the discussion into potential areas for further investigation and exploration.
- Chapter VI: Examine and analyze the outcomes in comparison to earlier research findings. Engage in a discussion regarding the results concerning their alignment or divergence with prior studies.

CHAPTER II

Literature Review

This chapter presents the theoretical frame and related works in the emotion recognition by EEG signal.

Related Research

Owing to massive proportional advancement in the range of machine learning algorithms, Thejaswini et al. (2019) proposed an approach for detection of emotions. It was proposed and resulted in this paper that a dimensional model could be implemented on the DEAP and SEED-IV datasets in providing improved prediction results. DWT was employed at the suggested technique to extract statistical information of the signals, frequency content and entropy respectively. Furthermore, they addressed method for classification of signals using the Support Vector Machine (SVM). They managed to achieve an accuracy of 79% for DEAP dataset and 76% for SEED-IV dataset as a result of the modifications made.

Mohammadi et al. (2017) presented how DWT is used to extract features from the EEG data. For the real-time emotion recognition, they proposed the Arousal-Valence Dimension model and used DEAP dataset. SVM and KNN, two different classifiers in this research but SVM and KNN both have acceptable level of accuracy. Especially, gamma, which has a high rate frequency and degree of accuracy in the classification results compared to other frequency components.

In the work described by Sarma & Barma (2021), they combined multivariate analysis with the aid of random matrix theory to find EEG regions with high emotional content. The most valuable advantage of this approach is that, when a certain segment is decided to be included, incorrect channels do not have to be erased, rather they are excluded, or the proper channels are selected. As a next step, PSD and CWT features extracted from the selected segments were further used to train and classify the data sets using KNN, SVM, and RF techniques on both DEAP and SEED databases.

Practical objectives of preprocessing algorithms used in traditional methods for EEG emotion extraction are often aimed at identifying unique EEG characteristics from various domains. Liu & Fu (Y. Liu & Fu, 2021), also conducted a study to diagnose a range of emotions using a technique called feature fusion which is the use of information from multiple sources simultaneously. To recognize emotions, they used the Support Vector Machine (SVM), and this study examined the properties of the EEG data in the temporal and frequency dimensions. They preferred the wavelet processing since it facilitated handling of the high dimensional EEG compound feature. To analyze the performance of this suggested model, DEAP dataset was used.

It was done by following the work of Mi Li et al. (2018) that splitted the DEAP dataset into four different frequency ranges and to measure the effect of different frequency and the number of channels on accuracy. The entropy and energy for each band were then calculated and used as feature inputs for the K-nearest neighbours (KNN) classifier. The analysis also revealed the general trend sounded the gamma frequency band signal has the highest categorization accuracy, regardless of involving valence or arousal component. In addition, the study revealed that the gamma band play a role different from the low band in the context of recognizing the emotional conditions and rejected the hypothesis of the significance of the delta band for the recognition of the mentioned aspects with regard to valence and arousal. Furthermore, they mentioned how the inclusion of more channels of EEG might boost the accuracy with regard to feelings state classification. It should be noted that through the constant development of the approaches combined with the ideas of deep learning, the DL modules could substitute any or all of the components in the system stated above. There are many types of networks that have been developed which include the Convolutional neural Networks (CNN) as discussed in (Gliner et al., 2021) and Long Short-Term Memory Networks (LSTM) developed by Hochreiter & Schmidhuber in 1997. There is existing research done in the field of emotion recognition using deep learning by Xiao and colleagues(Xiao et al., 2022) which proposed a CNN-based system for the same. To further analyze the characteristics of DE, EEG data were transformed in to the 4D format before obtaining its DE features. The next process involves using the CNN to extract spectral as well as spatial features throughout each temporal frame. Last, LSTM was applied for extracting basic features from the multiple segments, providing different weights for various Brain area and Frequency bands for unveiling the emotions of the segments. The proposed classification method was able to yield high classification accuracy. The study included using the data found in the DEAP and SEED databases.

To demonstrate the performance of the feature extraction methodologies mentioned above, and as per Cimtay & Ekmekcioglu (Cimtay & Ekmekcioglu, 2020), the researchers plan to employ CNN for accomplishing end-to-end emotion categorization. To also increase the accuracy in classification they had to enhance the model being used in this study by including more layers. The required preprocessing steps also involved the employment of a median filter to refine internally wrong detections within an emotionally predicted time slot to enhance the classification performance. In this connection, in the three datasets that Whitten and his team worked on, they achieved accuracy levels of 72. With the complexity of the DEAP dataset, the accuracy is 81 percent while with the complexity of the using dataset the accuracy is 81 percent as well. Were 78% for the LEXIS dataset, 79% for the LEXUS dataset, and 8% for the LUMED dataset, and 86.19% on the SEED dataset, while the suggested approach gained a mean accuracy of 56%.

In addition, the researchers adopted three different methods of data collection and integration, which include (Zali-Vargahan et al., 2023) . They also stated that the proposed FaDFR method establishing minimized profound time-frequency attributes from EEG recordings based on the Inception-V3 CNN for high attributes learning and support vector machine (SVM) for pattern categorization offered the best solutions. For the DEAP database, accuracy rates of 88% were attained. For the ORL dataset, the results were 6% and 94.60.83%, and for the SEED dataset, 58%.

The study of Gao et al. (2020) discussed the creation of a technique for nonlinear estimations and for feature extraction from the frequency bands for recognizing the emotions embedded in the EEG information. This was made possible by a convolutional network that entailed an integration of multiple channels of information. The model adopted a 1D convolutional layer that measured spatial dependencies of the electrodes and weighted linear combinations from contextual information including the features of DEAP and SEED datasets. It was designed to filter out a large amount of artifacts from real-world EEG data while modeling time dependence and electrical interactions among sensors.

A different method for emotion detection was presented in a recent work described in (Xing et al., 2019), which used multichannel EEG data as a basis. To make the accuracy of emotion categorization, the method combined a linear EEG model with a model of emotion timing. This improvement made it easier to understand EEG data accurately in relation to other cases.

Techniques such as signal structuring, Hanning window, and power spectral density utilized to gain attributes from the dataset. Using the DEAP dataset, classification accuracy rates were 81.10% for valence and 74.38% for arousal.

A hybrid model that merges CNN-LSTM was designed to provide a deep learning framework designed especially for feeling detection in an individual study (Tao et al., 2020). The DEAP and DREAMER datasets were utilized in the implementation of this model. The goal was to examine into spatial information by utilizing CNN and channel-wise attention procedures. Moreover, the ACRNN (Attention-based Convolutional Recurrent Neural Network) method integrated an increased form of self-attention with RNNF (Recurrent Neural Network Fusion) to assess the temporal properties present in EEG data.

Different frequencies were extracted from the EEG data in the study by Iyer et al. (2023) using differential entropy (DE). Following feature processing, these features were fed into the CNN-LSTM models. By fusing sub-blocks from the CNN and LSTM algorithms, the fused model was developed. They achieved accuracy rates of 65% on the DEAP database and 97.16% on the SEED database.

An innovative technique for classifying multi-spectral topographical pictures created from EEG data was introduced by the study conducted by Ozdemir et al. (2021). For feature extraction, LSTM was used to collect temporal properties within the time span. These multi-spectral topography pictures were created using the electrode locations and EEG signal frequency bands from the DEAP database. The spatial, temporal, and spectral EEG data were successfully maintained in these pictures, making them useful for study. The results of this investigation showed impressive accuracy rates of 86.13% for valence and 90.62% for arousal classifications.

In order to provide a straightforward way of automatically identifying emotions using temporal features, a parallel CNN-LSTM architecture was developed (Ramzan & Dawn, 2021). To accomplish the recognition of both positive and negative emotions, this recently proposed model was applied to the DEAP and SEED datasets.

The autoencoder is a popular nonlinear approach for dimensionality reduction. Unlike CNNs, which have localized structures, and LSTM networks, which lack important memory retention capacities, attention mechanisms allow for the modeling of relationships across distant points in a sequence. Two fundamental components make up a recently created deep learning architecture (Arjun et al., 2022) intended for applications that are independent of the subject. Firstly, it was suggested to use LSTM in conjunction through a channel-attention autoencoder to generate subject-independent implicit variables subspaces for specific subjects. Secondly, a CNN integrated with an attention mechanism designed to do subject-independent emotion identification, getting from the previous phase. This approach has been assessed on the DEAP, SEED, and CHB-MIT database.

In different study (Algarni et al., 2022), an approach was used to enhance accuracy and performance in recognizing emotions, especially by applying a stacked Bidirectional Long Short-Term Memory (Bi-LSTM) model on the DEAP dataset. In order to reduce the learning and generalization phases of the model and limit the possibility of overfitting, feature extraction method were employed. By extracting statistical, wavelet-based, and Hurst exponent-based information, the model's effectiveness was improved. The BGWO (Binary Grey Wolf Optimization) approach was used to address the dataset's complexity and high dimensionality, leading to a decrease in identifying time and an enhancement in framework efficacy.

A combined recurrent neural network with highly linked layers was suggested by the researchers in the study that was presented (Garg et al., 2019). The model utilized advanced techniques for deep learning involving dropouts, LSTM cells, and the Rectified Linear Unit (ReLU) activation function to impede potential data overfitting. Furthermore, problems with vanishing gradients and short-term memory were effectively solved by the implementation of the model. On the DEAP dataset, the model involved a wavelet transform for feature extraction as well as statistical measurements, and a merged LSTM for classification was used.

The difficulty of combining models within the framework of deep learning has been investigated by the researchers (Yin et al., 2021). Graph convolutional neural networks (GCNNs) have been employed in a model that fuses to extract features from the graph-based domain. The extraction of temporal characteristics was made easier by the use of LSTM cells, which were also used to recognize how the correlations between pairs of EEG channels changed over time. Then, using the extracted features as a basis emotion, a dense layer was used to conduct emotion classification. The results demonstrated the suggested approach's higher classification performance on the DEAP dataset when compared to other approaches. To give weight to emotional states that appear at certain moments, an attention weight mechanism was designed. This technique assisted in determining the most significant input component, increasing its relevance during network training as its importance arose.

In order to evaluate the DEAP dataset, Y. Kim & Choi, (2020), presented a hierarchical strategy combining CNN and LSTM models with an attention mechanism. The methodology involved a direct end-to-end classification of emotions without the need for signal feature extraction. According to the evaluation of this method, there was less information loss than is generally seen throughout the feature extraction procedure.

The strategy described in (H. Yang et al., 2019) offers a significant reduction in this impact given that the dynamic nature of EEG data impacts decision-making. This approach relies on weighted voting to arrive at the final decision. Yang presented a multi-column CNN structure for EEG-based emotion recognition. Each model component is designed as a CNN-based emotion detection module with fully linked layers, convolutional operations, and pooling. The DEAP dataset is utilized as the model's input dataset.

A novel method for classifying emotional characteristics using EEG recordings was presented in (Mu Li & Member, 2009). This study's main goal was to produce automated fuzzy classification rules based on EEG data. The suggested method employed Fuzzy C-Means (FCM) clustering to generate a collection of guidelines derived from the EEG recordings. Significant improvements in computing efficiency were made by utilizing the suggested fuzzy emotion classifier and the related extraction method. This is due to its rule-building and data-driven learning methodology. The three-dimensional human emotion models show that the FCFCM technique is applicable across all of their dimensions. The results showed that the technique performed more accurately than that of Support Vector Machines (SVM) and fuzzy classification applying predetermined parameters, reaching accuracy rates of 55.77%, 49.62%, and 54%, respectively.

Using a variety of methods and techniques, the proposed framework is designed to provide a more comprehensive and accurate comprehension of the emotions. The suggested approach uses signals as the first inputs for a convolutional neural network (CFNN). It consists of a layer that converts flattened features from the convolutional layer into fuzzy quantities, or fuzzification, and a subsequent layer that defuzzifies fuzzy sets into crisp values. Fuzzy neural networks, which can generate both exact and fuzzy values, are used in the proposed method to improve classification accuracy. It implies that fuzzy sets might have more information, which would increase accuracy. Furthermore, the approach excels at controlling data disturbance caused by noise.

CHAPTER III

Methodology

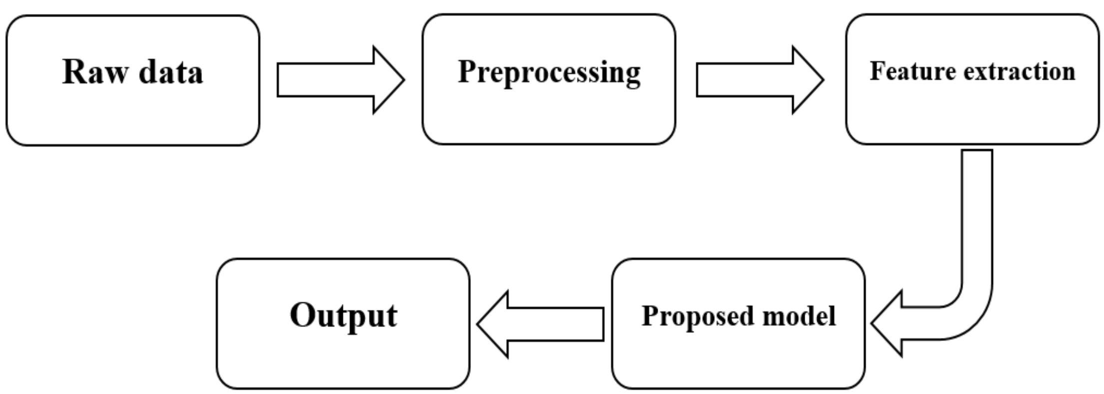
This chapter includes details on dataset, modelling methods, analysis approaches.

Method

The algorithm for emotion recognition from EEG signals is provided in Figure 1. After collecting the dataset, the raw data was preprocessed. Following it, the important features were extracted from the data. And the future extracted vectors are input to the proposed model for classification and detection of emotion.

Figure 5.

The flowchart of emotion recognition through EEG signal.



Dataset

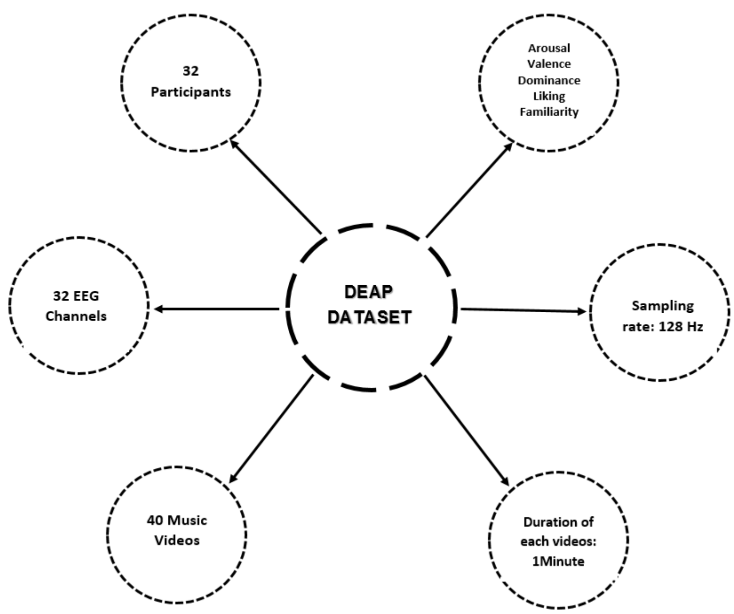
In our research, we examined a highly advanced DEAP dataset (Koelstra et al., n.d.) which is widely recognized as a benchmark and used dataset for evaluating feeling detection. The DEAP database allows us to evaluate the accuracy of the gained attributes and the effectiveness of the algorithm we have proposed.

The database includes 32 participants, evenly split between males and females, who viewed 40 different videos designed to elicit various emotional responses. EEG data was collected from the subjects using the Biosemi ActiveTwo device while they watched the clips. After each video, the participants used a survey according the Likert scale that ranged from 1 (which is low) to 9 (higher) to report their levels of arousal, valence, dominance, liking, and familiarity. To ensure the precision and dependability of the outcomes, the research was verified by one dataset, primarily because there were sufficient findings available for every participants in the feeling recognition methodology.

The DEAP database has been pre-processed and is readily available to researchers for their utilization. This dataset employs clip videos as stimuli to induce emotional responses. The signals were originally recorded at 512 Hz and then resampled to 128 Hz. In this study, the methodology used comprises a 2D emotional model that encompasses valence and arousal. Valence qualifies the positivity or negativity of an emotion, while arousal signifies the intensity of associated emotions, including the level of excitement or indifference. Figure 3.2 depicts the general representation of the DEAP dataset.

Figure 6.

Descriptive overview of the DEAP dataset.

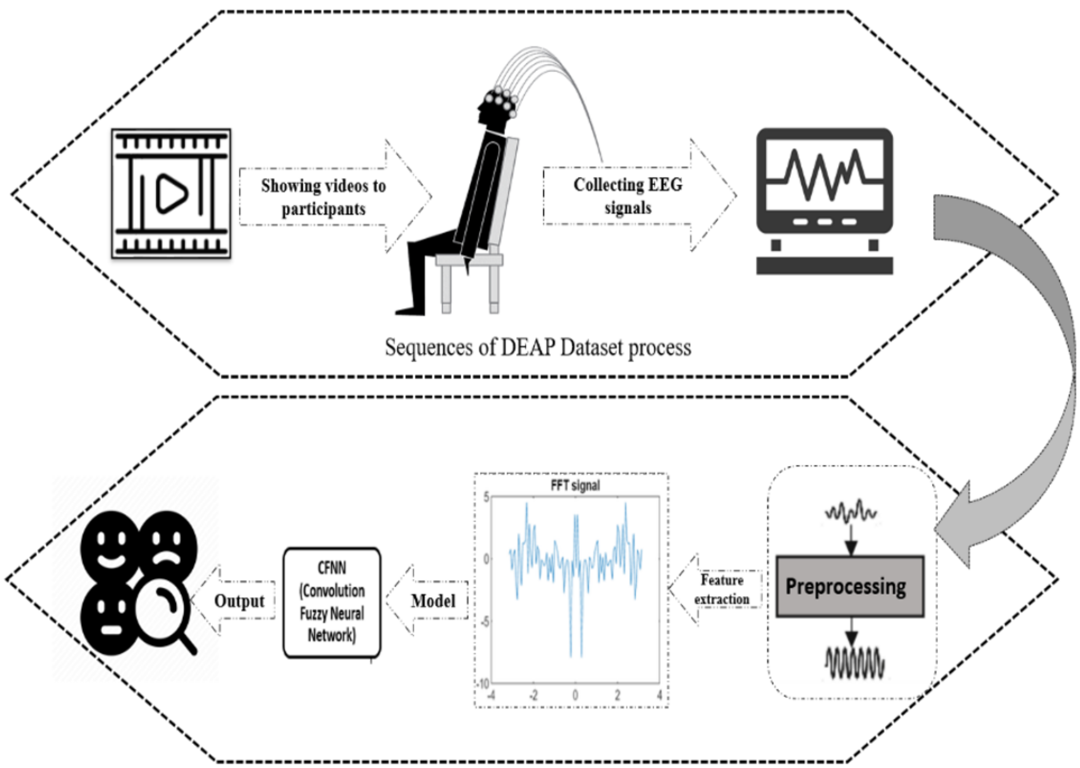


Proposed Method

The proposed approach involved a sequence of steps, starting with noise and artifact reduction in the pre-processing stage, following by feature extraction to acquire relevant training data, and enhancement of the CFNN for emotion classification. Figure 3.3 provides a concise overview of the proposed model.

Figure 7.

Descriptive overview of the DEAP dataset.



Pre-processing and Feature Extraction

Despite the fact that the DEAP database was made available in a pre-processed form of its original EEG recordings, it still contains unwanted artifacts and various noises that have the potential to interfere with the analysis. In this research, the experiments involved the use of EEG signals from 32 individuals who watched 40 videos within the DEAP dataset, collected through 32 channels. These EEG recordings were initially down-sampled to 128 Hz to capture precise information within the frequency range of 0-48 HZ (Koelstra et al., n.d.). The down-sampled EEG data was cleansed, and additional component in the signal, like slow wave patterns, were extracted from the analysis through the application of a bandpass filter.

Among the fundamental but complex aspects of human feeling detection, which varies with changing emotional states, is the identification of suitable features and characteristics (Wagh & Vasanth, 2019). The effectiveness of the detection of feelings is significantly impacted according to how well-made the attributes, understanding the significance of extracting attributes that exhibit a strong correlation with emotions and provide a precise and reliable representation as a central element of emotion recognition (Jianhua Zhang et al., 2020). Feature extraction is a method that may reduce the number of dimensions in the attribute area by either pinpointing the best attributes for categorization identification from a large dataset of attributes information or by creating a set of few but highly accurate attributes possessing a remarkable low likelihood of categorization error. Every attributes obtained from a signal offers distinct insights into the data and characterizes the behavior of signals. Extracting features method aims to present an algorithm with less attributes while maintaining higher accuracy (H. Liu et al., 2021).

A widely employed signal processing method for transforming time based signals into frequency based signals is Fourier analysis (Murugappan, 2013). In this study, Fourier transformations are utilized to decompose the EEG signal into its constituent frequency components (Nandini et al., 2023). The Fast Fourier Transform (FFT) method, which computes the Discrete Fourier Transform (DFT) of a sequence, is a commonly employed technique for calculating the Fourier Transform. It produces identical results to directly assessing the DFT description, but it is considerably more rapid. The equation for the DFT is provided in Equation (10).

$$X_k = \sum_{i=0}^{N-1} x_i(n) e^{\frac{-j2\pi ik}{N}} \qquad for\ k = 0,1,2 \ldots N-1$$

(10)

X_k represent the discrete Fourier coefficient, N stands for the size of the available data, and $x_i(n)$ is the temporal domain of the incoming data (Singh & Singh, 2014). By transforming the signal function into the frequency range using Equation (FFT), one can establish the fraction of a signal's frequency elements that could be insufficiently determinable in the time domain. (Akter et al., 2022).

In this research, the FFT is employed to process data from the original EEG database, taking into account the window size. For each of the patients, all raw values from the 40 electrodes in the DEAP dataset are uploaded at first. Afterward, the chosen 14 electrodes of EEG recordings are collectively shown. Ultimately, the visual depiction of every 14 EEG recordings channel is exhibited throughout the subsequent stage. In the fourth phase, employing five distinct power bands, the FFT procedure showed how the signal from every single channel was transformed into a frequency domain. As demonstrated by Table 1, an overall of 14 channels have been chosen for this study. The final phase reveals the unified frequency domain of these 14 channels. Following the gaining attributes procedure, the extracted attributes were input into the proposed model for the purpose of classification.

Table 1.

Parameterized FFT explanation

Chosen Channels		1,2,3,4,6,11,13,17,19,20,21,25,29,31 (Mi Li et al., 2018)
Bands	Theta	4-8 Hz
	Alpha	8-12 Hz
	Beta(lower frequency)	12-16 Hz
	Beta(higher frequency)	16-25 Hz
	Gamma	25-45 Hz

The Proposed Convolutional Fuzzy Neural Network Model

Convolutional Neural Network

CNN plays a major role in the deep learning field, serving as a highly potent technique for image analysis. Its strength lies in extracting features within its convolutional layers and subsequently categorizing these attributes in the fully-connected layer. The utilization of one-dimensional CNN (1D-CNN) has become notably valuable in feature extraction based on time series information and establishing resilient estimates (Zamani & Wulansari, 2021). This has propelled 1D-CNN as a favored method for scrutinizing sequential data, notably EEG signals.

Before implementing the fuzzification process, we utilized 1D-CNN to gain the attributes from EEG recording and forecast features.

Fuzzy Neural Network

The Fuzzy Neural Network, combining the advantageous aspects of both fuzzy logic and neural networks, stands as a fundamental technique for intelligent information processing (Gai & Hu, 2018). Therefore, the technique of fuzzy neural networks holds substantial potential for both autonomous analyzing information via self-learning and effective illustration for architectural details. A system employing a numerous inputs fuzzy neural network assesses each input component based on its membership in various fuzzy sets. Consequently, an input to the system generates a fuzzy output rather than a crisp value. Subsequently, the system can execute fuzzy inference by applying pre-established fuzzy rules.

The design of the FNN incorporates fuzzy rules formulated in the "If-then" structure, as depicted in Equation (11):

$$P_j = IF\ u_1\ is\ P_{1j}\ \dots \wedge\ u_n\ is\ P_{nj}\ , THEN\ y_j =\ w_j$$

(11)

In this context, P_j signifies a fuzzy rule, P_{ij} signifies fuzzy sets, and w_j refers to a zero-order Takagi-Sugeno-Kang weight. The description of the fuzzy set P_{ij} , incorporating a Gaussian membership function, is represented in Equation (12):

$$P_{ij} = exp\left\{\frac{-(u_{1-}\ m_{ij})}{2\sigma_{ij}^2}\right\}$$

(12)

Where the function exp (.) denotes the exponential function, while m_{ij} and σ_{ij} represent the mean and standard deviation of the fuzzy set P_{ij}, respectively.

The CFNN model represent a neural network framework that fuses elements of fuzzy logic with the principle of CNN. It has been specifically designed for processing data that includes uncertain or fuzzy values. The structure we suggested integrates the CNN's extracted features with the fuzzy processing capabilities of the FNN. This approach combines the advantages of both network design.

The approach of adding a fuzzy layer is described as fuzzification which converts the input matrix into the fuzzy layer. This transformation allows for the extraction of high-dimensional features through a convolutional representation of the outcome. Subsequent to passing through the fuzzification process, the converted features become crisp values. The CNN model is enhanced with an extra defuzzy layer and the process commonly referred to as defuzzification. The fully connected layer received information from the defuzzy layer and performed the classification. The estimation of the fuzzy set is conducted following the provided Equations (). Assuming X is the input matrix. The equations (13-14) illustrate the probabilities of the each element present in the domain of fuzzy numbers.

$$\hat{X} = Fuzzification\ (X_{i,j} \mid cx_{i,j}) \tag{13}$$

$$x_{i,j} = possibility\ \left(x_{i,j} \mid MF_{i,j}\right) = max\ MF_{i,j}\ \delta(x - x_{i,j}) \tag{14}$$

In this context, 'i' and 'j' correspond to the indices of the elements within the input matrix X, while 'cx' stands for the central value of the input fuzzy membership function. The expression $\delta(x - x_{i,j})$ denotes the Kronecker delta function. The defuzzification process determines the crisp value ν_i in accordance with Equations (15-16). The fully connected layer is used as last classifier by receiving the crisp result value from the defuzzification process.

$$\nu_i = defuzzy\ (x_i) = \frac{\sum C_y\ x_i}{\sum x_i} \tag{15}$$

$$y_i = W_{fc}\, \nu_i \tag{16}$$

C_y signify the main component of the defuzzification membership function, while the weight allocated to the fully connected layer is designed as W_{fc}. The layer called pooling comes after the feature extraction procedure. It represent statistical data from adjacent to results in a brief way. This stage improves the representation, ensuring it remains consistent even with input shifts, and it can potentially reduce the input dimensions for the subsequent fuzzy convolutional layer.

$$y_{ij} = \sigma\ (x_{ij}) \tag{17}$$

While $\sigma(.)$ denotes the activation function of the convolution layer (Equation (17)). Calculating the output probability for classification uses the softmax function. The softmax equations are presented as follows in Equation (18):

$$y_i = Softmax\,(d_i) = f(d_i) \tag{18}$$

The loss function layer assesses the cost or penalty associated with what is expected and the actual data labels. Many loss function are available, each suitable for a certain need. The backpropagation technique is employed when a loss function detects a substantial divergence and produces an error. CNN efficiently lowers dimensionality without losing details, while at the same time, fuzzy logic improves data consolidation by eliminating noise. The integration helps identify key data features and controls the large variance of the data. The convolutional layers are created to acquire and extract significant features from the input training data. The result of the convolutional layers is combined with fully connected layers, which extract the feature data. Contrary to fuzzy neural networks, which have feature maps that contain fuzziness or uncertainty, conventional neural networks' feature maps are made of crisp values for each pixel.

The method we employed involved merging a fuzzy neural network with a convolutional neural network. Figure 3 illustrates the architecture of the convolutional fuzzy neural network. The model comprises a total of 9 layers, which encompass 2 Conv 1D layers, 1 max pooling layer, 1 flatten layer, a fuzzy layer, a batch normalization layer, a dense layer, a defuzzy layer, and dense layers concluding with a softmax output layer.

Figure 8.

Architecture of CFNN model

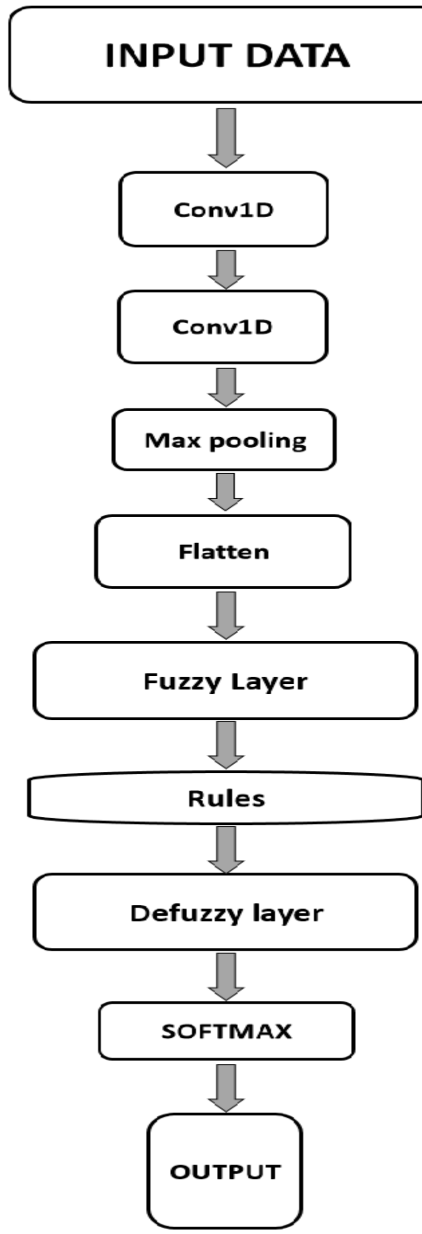


Figure 3.4 illustrates the overall configuration of the proposed CFNN model, while Table 2 provides an extensive breakdown of the parameters and layers within this model.

Table 2.

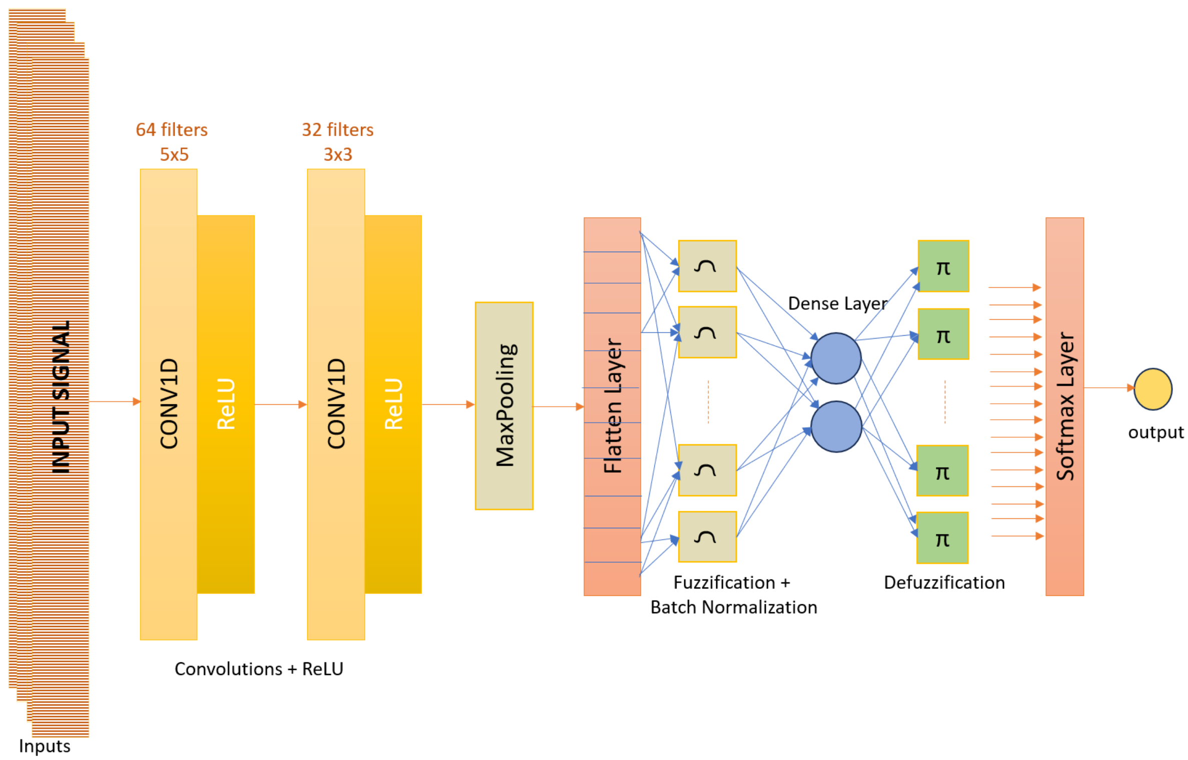
Comprehensive details regarding the layers of the suggested model

No	Layer	Filter/Kernel/Node	Output shape	Param#
1	Conv1D	64 / 5x5 / -	(None, 73, 1)	384
2	Conv1D	32 / 3x3 / -	(None, 73, 64)	6176
3	Max pooling	-/-/-	(None, 73, 32)	0
4	Flatten	-/-/-	(None, 1152)	0
5	Fuzzy	-/-/-	(None, 2)	4608
6	Batch normalization	-/-/-	(None, 2)	8
7	Dense	2	(None, 2)	6
8	Defuzzy	-/-/-	(None, 2)	4
9	Activation	-/-/-	(None, 2)	0
Total parameters:	11186			
Trainable parameters	11182			
Non-trainable parameters:	4			

The feature extraction part consists of both conventional and max pooling layers. Additionally, a FNN is employed for classification, functioning similarly to a fully connected layer. The FNN provides the feature information from each fuzzy map. Fuzzy maps are maps that have a fuzzy set membership function. To merge the feature data, a fuzzy neural network with partially connected layers was utilized.

Figure 9.

The configuration of the suggested Convolutional Fuzzy Neural Network.

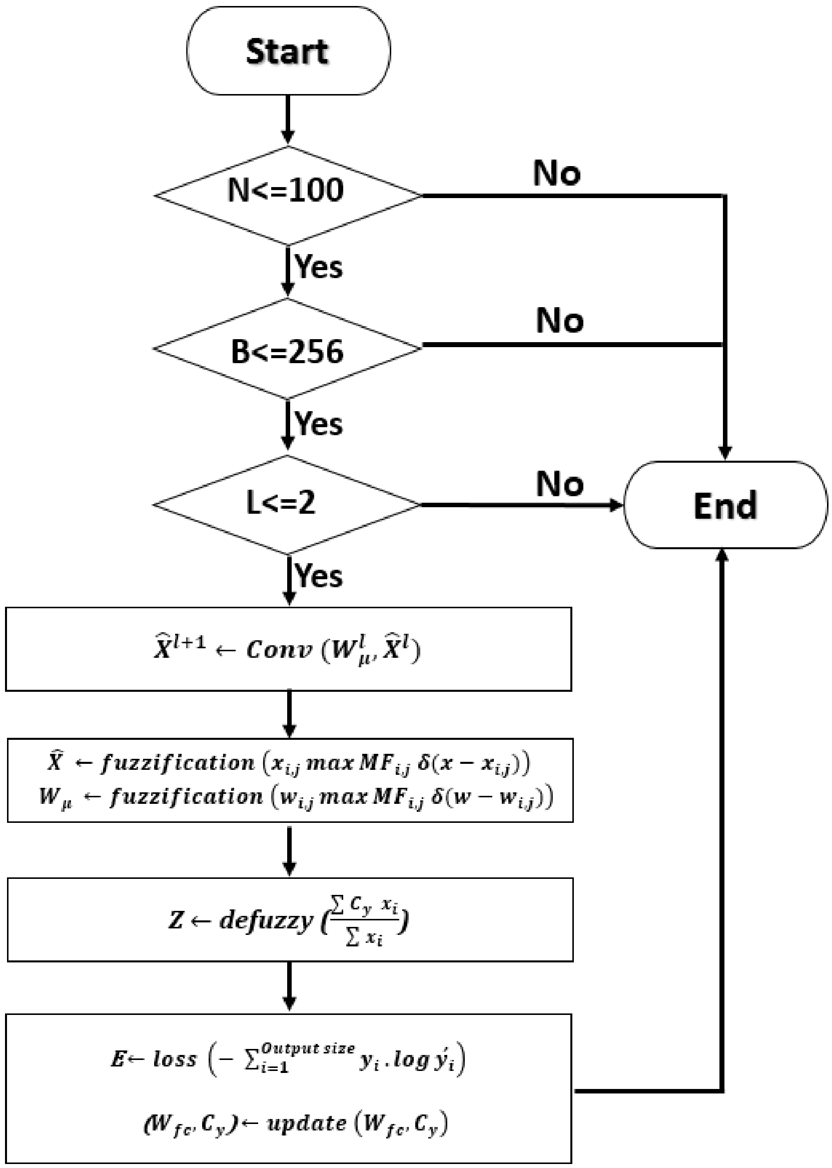


In the suggested method, following the extraction of features, the signals are fed into the model, passing through a CONV1D. CNNs are tasked with extracting essential features from the data in order to provide precise predictions. The framework employs two CNN layers. After applying the CNN kernel, the outcomes are forwarded to a max-pooling layer, which selects relevant features and speeds up calculations. This approach provides savings in time required for computation as well. The final result is flattened and subsequently transmitted to the fuzzification layer. Figure 3.5 is depicted the structure of the proposed model.

The Fuzzy layer takes the input and carries out operations based on the fuzzy rule applied to the flattened outputs. The fuzzy rule neurons absorb the fuzzification neurons. Within this layer, the weight of each rule is evaluated, resulting in an output derived from the input signal. The output from this layer is transmitted to the normalized layer. The final layer, known as the defuzzification layer, produces the crisp output from the CNN combined with the fuzzy layer. The result is hen sent to the softmax layer to be classified as valence and arousal in the following phase. The flowchart for training the CFNN model is shown in Figure 3.6 Training dataset X and associated labels Y are the input's components. Furthermore, it includes parameters such as batch size (B), dropout rate, the number of training epochs (N), and the quantity of convolutional layers (L).

Figure 10.

The configuration of the suggested Convolutional Fuzzy Neural Network.



CHAPTER IV

Findings and Discussion

This chapter provides an overview of the outcomes achieved through the application of the proposed model.

Measurement of the model

The proposed approach was executed on a personal computer equipped with an Intel (R) Core (TM) i5-5200U CPU running at 2.20GHz, 64GB of RAM, and an NVIDIA GeForce 840M graphics card. The model was deployed in Google Colaboratory, a hosted Jupyter Notebook service. The Python version utilized was 3.10.12, and the TensorFlow version employed was 2.12.0.

The categorization process involves two main stages: training and testing, during which the classification takes place. The training and testing sizes were set at 75% for training and 25% for testing to ensure accuracy. The training data has dimensions of 32×32×40×8064, while the training labels are of size 32×32×4. Similarly, the test data is sized at 32×8×40×8064, and the test labels have dimensions of 32×8×4.

The model's real performance, however, might be confusing because accuracy is shown without precision. Equation (19) represents the measurement of accuracy.

$$\text{Accuracy}=\frac{TP(True\ Positives)+TN(True\ Negatives)}{TP(True\ Positives)+FP(False\ Positives)+TN(True\ Neatives)+FN(False\ Negatives)} \quad (19)$$

FP stands for the count of incorrectly classifying low states, FN represents the count of incorrectly classifying high states, and TP signifies the count of accurately determining arousal and preference for low-state samples using the classification method.

Precision and recall serve as valuable metrics for evaluating prediction accuracy in situations where there is a significant class unbalance. Recall assesses the overall count of relevant outcomes, whereas in information retrieval, precision signifies the relevance and significance of the results (Equation (20)).

$$\text{Precision}=\frac{TP(True\ Positives)}{TP(True\ Positives)+(False\ Positives)'} \tag{20}$$

Recall is also described by Equation (21):

$$\text{Recall}=\frac{TP(True\ Positives)}{TP(True\ Positives)+(False\ Negatives)'} \tag{21}$$

The F-score, a metric that combines both recall and classification accuracy, is calculated as per Equation (22):

$$\text{F1 Score}= \frac{2 \times Precision \times Recall}{Recall+Precision} \tag{22}$$

Equation (13) is the formula used to determine the cross-entropy loss for the classification of multiple classes:

$$loss = -\sum_{i=1}^{Output\ size} y_i \,.\log \acute{y}_i \tag{23}$$

$\acute{y}_i$ is a single numeric value, y_i represents the intended target value, and the output size corresponds to the overall number of values in the model's output.

Results

Besides the enhanced FCNN approach proposed, we conducted training for SVM, KNN, 1D-CNN, and Bi-LSTM for binary emotion classification (arousal and valence) to offer a comparable analysis. Using 75% of the obtained feature data as training data and setting reserve 25% for testing, all algorithms were trained. The proposed algorithm was configured with a learning rate of 0.01, a batch size of 256, and utilized the Adam optimizer. Following 100 epochs, the training process eventually came to an end.

Several training and testing ratios were employed, including 90-10%, 80-20%, and 75-25%. The FFT window width varied from 4 to 128 and was doubled in each trial. To ensure reliable findings, a 5-fold cross-validation analysis was conducted on the suggested model in addition to the hold-out tests.

During training using various training and testing ratios, the most elevated accuracy, F1-score, and precision emerged from the 5-fold cross-validation experiments (K=5), where all data were segregated into distinct training and testing folds. The top recall and second-best scores in other metrics were attained with a 75:25 training and testing ratio. None of the other hold-out ratios surpassed the scores achieved in the K=5 setting. To expedite analyses and reduce training time based on these findings, the subsequent experiments were conducted using a 75:25 hold-out ratio. Table 3 outlines the outcomes from both the hold-out and K=5 experiments.

Table 3.

Evaluation of efficiency of the suggested CFNN with different train/test splits.

Train/Test	**Results**			
	Accuracy	**Precision**	**F1-score**	**Recall**
90:10	96.94%	95.93%	96.43%	96.93%
80:20	96.85%	96.25%	96.49%	96.73%
75:25	**97.24%**	**96.47%**	**96.79%**	**97.12%**
K=5	**97.79%**	**97.70%**	**97.67%**	**96.98%**

Training the suggested model with various window sizes (4, 8, 16, 32, 64, 128) resulted in varying detection rates. The fluctuations posed challenges in determining the most effective and informative window size; nevertheless, it's important to highlight that window sizes of 4 and 8 might not be optimal for emotion classification. Table 4 showcases the outcomes yielded by the suggested algorithm utilizing diverse window lengths.

Table 4.

The suggested CFNN's effectiveness with various window sizes.

Window size	Accuracy	Precision	F1-score	Recall
4	97.06%	96.50%	96.58%	96.67%
8	97.24%	96.47%	96.79%	97.12%
16	97.36%	94.85%	96.87%	**98.98%**
32	97.88%	**99.12%**	**98.15%**	97.19%
64	**98.54%**	96.47%	96.79%	97.12%
128	**98.70%**	**99.01%**	**98.49%**	**97.98%**

With a window width of 32 and a training and testing proportion of 75:25, the suggested CFNN model produced F1 scores of 98.39 for valence and 97.93 for arousal after the hold-out and window length trials. With merging approaches, this model demonstrated improved classification performance, averaging 98% accuracy. Fuzzy logic's capacity to replicate human thought processes may be responsible for the enhanced efficiency. By periodically adjusting the weights, it mitigated overfitting and produced optimal results. Table 5 displays the accuracy, precision, recall, and F1-score outcomes for valence and arousal obtained by the proposed model using the DEAP database.

Table 5.

Effects (in 75–25%) of the suggested CFNN approach on the DEAP database.

Model	Emotion	Precision	Recall	F1-Score	Accuracy
CFNN	Valence	98.57	98.21	98.39	98.21
	Arousal	96.78	99.11	97.93	98.08

Among the comparative methods examined, it was evident that SVM and KNN did not accurately classify emotions utilizing the gained attributes. SVM yielded 55% and 54% accuracy for valence and arousal, whereas KNN achieved 61.00% and 60.00%, respectively. Although the Bidirectional-LSTM improved recognition rates with 72.01% for valence and 70.42% for arousal, it did not surpass the performance of 1D-CNN. From these methods, 1D-CNN delivered notable outcomes (88.87% for valence and 83.35% for arousal). Nonetheless, the proposed method obtained optimal results, reaching 98.21% and 98.08%, respectively. Table 6 illustrates the results garnered from the comparative study with state-of-the-art methods, while Figure 4.1 provides a visual representation of these outcomes.

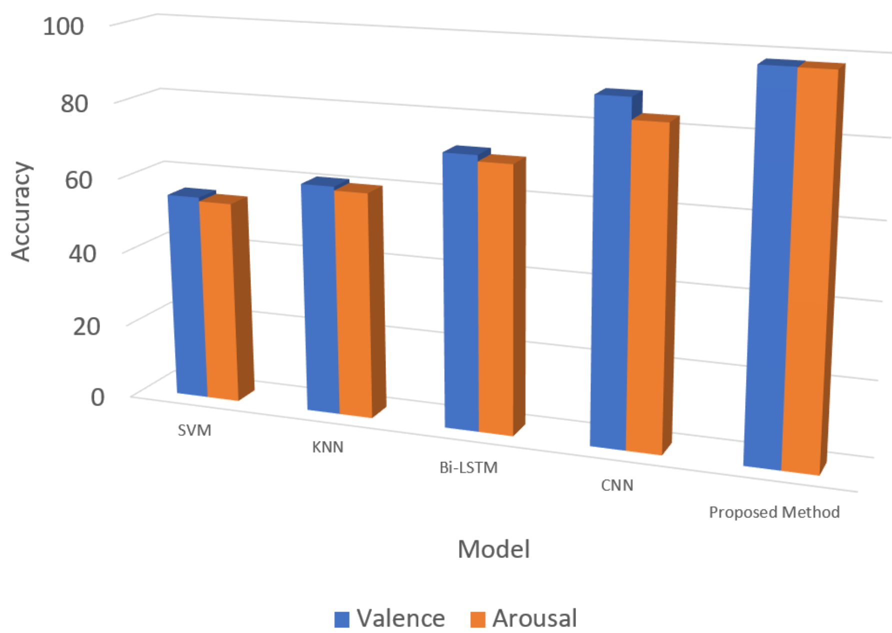
Table 6.

Results of comparing the suggested CFNN method with state-of-the-art techniques

	Accuracy (%)	
Model	**Valence**	**Arousal**
SVM	55.00	54.00
KNN	61.00	60.00
Bi-LSTM	72.01	70.42
CNN	88.87	83.35
Proposed Method	**98.21**	**98.08**

Figure 11.

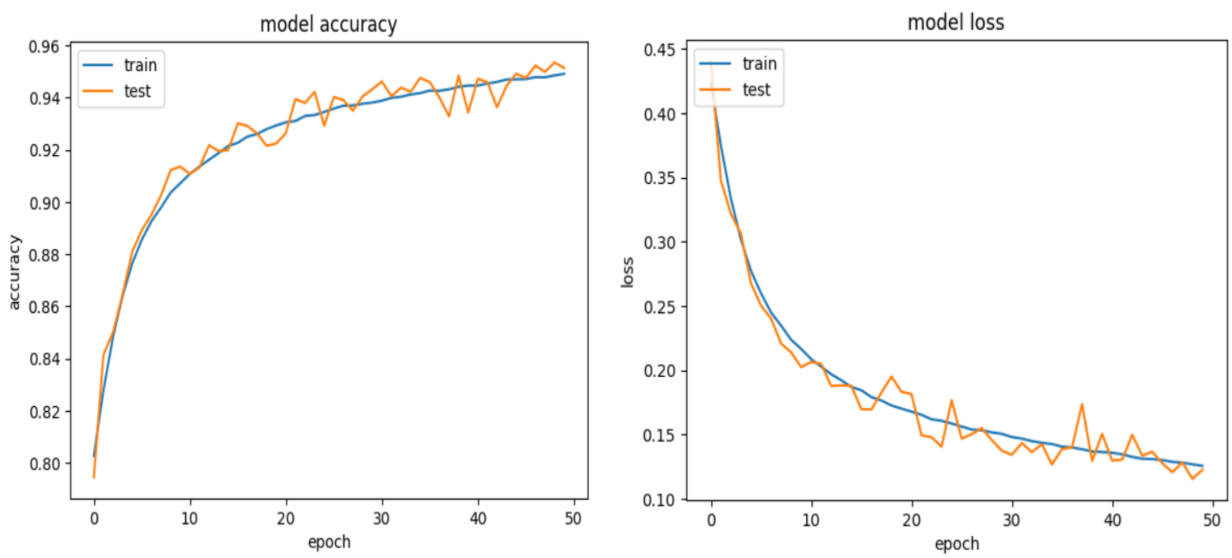
Graphical visualization of comparison results.



Figures 4.2 and 4.3 depict the improvement in loss and accuracy when combining CNN and fuzzy logic. Since the CFNN model demonstrated improved handling of noisy data, it resulted in a decrease in disruptions caused by noise during the classification process.

Figure 12.

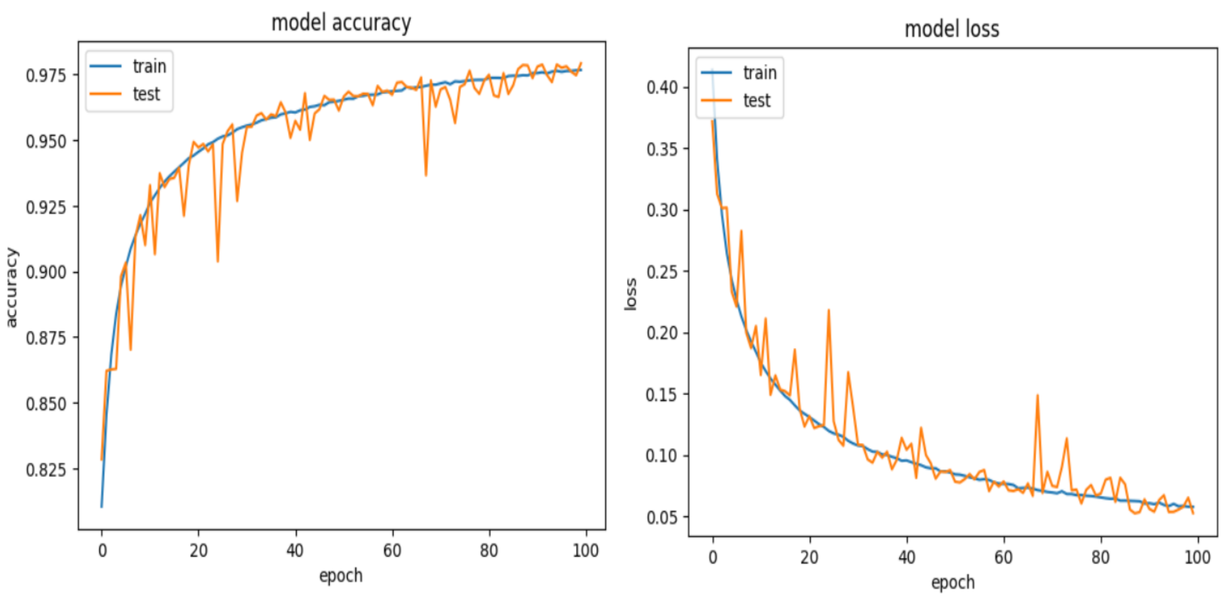
Model test and train graph: (a) Accuracy graph of model in valence; (b) Loss graph of model in valence



(a) **(b)**

Figure 13.

Model test and train graph: (a) Accuracy graph of model in arousal; (b) Loss graph of model in arousal



(a) **(b)**

Although the suggested model attained outstanding accuracy, it's possible that extending the training dataset could impact the model's efficiency. Understanding the model's performance over various training sizes is crucial. Table 7 illustrates an instance of experimenting with diverse partitioning schemes for training and testing, stating the durations for both training and testing in each split. In addition, the suggested model was tested for 5-fold cross-validation. Wall time represents the elapsed time between the initiation and completion of a particular process, as indicated by a wall clock or a handheld stopwatch. The time spent executing user code is referred to as "user-CPU time," whereas the time spent executing kernel code is referred to as "system-CPU time." Among the options for splitting the training and testing data, the 75-25 division yielded the highest test accuracy, reaching 97.24%.

Table 7.

Performance report for varying train/test splits.

Train/Test Split		Time			parameters			
		User	System	Wall	Accuracy	Precision	F1-score	Recall
10%	90%	12.75 s	399 MS	20.8 s	96.94%	95.93%	96.43%	96.93%
20%	80%	20.6 s	809 MS	18.3 s	96.85%	96.25%	96.49%	96.73%
25%	75%	31.3 s	1.19 s	28.3 s	97.24%	96.47%	96.79%	97.12%
K=5		33.9 s	1.26 s	41.2 s	97.79%	97.70%	97.67%	96.98%

CHAPTER V

Discussion

This chapter extensively discusses the study findings, comparing them with existing literature. We thoroughly explore how deep learning modeling approaches, along with pre-processing and relevant methodologies, impact the detection abilities of the models.

Discussion

In a recent study by Al-Nafjan et al., they employed Power Spectral Density (PSD) as the feature extraction technique and utilized Deep Neural Networks (DNN) for classification purposes. Their results demonstrated an accuracy of 82% for both valence and arousal categories, showcasing the potential of this method in emotional classification (Al-Nafjan et al., 2017).

Alhagry et al. used LSTM to extract features from the signals. Their findings revealed impressive accuracy levels, recording 85.45% for valence and 85.65% for arousal. This approach highlights the efficacy of LSTM in understanding emotional nuances captured in the signals (Alhagry et al., 2017).

Xing and colleagues in their research, referenced as Xing et al., utilized a combination of SAE and LSTM-RNN to address the issue of linear EEG signals. Through their approach, they achieved accuracies of 81.10% for valence and 74.38% for arousal. This technique proved effective in mitigating the challenges associated with these EEG signals, showing promising results in both valence and arousal recognition (Xing et al., 2019).

Iyer and colleagues, in their study, introduced a hybrid model integrating CNN and LSTM. Their model utilized DE (Differential Evolution) for feature extraction, resulting in an achieved accuracy of 65%. This approach, combining convolutional CNN with long short-term memory LSTM, and employing DE for feature extraction, demonstrated a noteworthy 65% accuracy (Iyer et al., 2022).

Sharma and colleagues conducted an investigation into emotion classification, specifically focusing on valence and arousal. Their methodology involved utilizing PSD for feature extraction. Through the implementation of CNN and LSTM models, their results revealed significant accuracy percentages. For valence, the CNN model achieved an 85.23% accuracy, while the LSTM model surpassed this with an 87.68% accuracy. Similarly, for arousal, the CNN and LSTM models achieved 86.50% and 87.98% accuracy, respectively (Sharma & Meena, 2023).

In a highly impactful study, Singh and colleagues, referenced as Singh et al. [49], crafted a classification model employing a combination of CNN 1D and Bi-LSTM. Their model yielded remarkable results, achieving an accuracy of 92.29% in one class and 90.33% in another (Singh & Singh, 2014).

Yang et al.'s exploration introduced a multi-column structure within their CNN-based model, showcasing a method designed for heightened accuracy in assessing emotional states. Their achieved accuracies, notably high in both valence and arousal, highlight the effectiveness of their approach. This emphasizes the potential of their multi-column structure as a pivotal enhancement in CNN-based models, illustrating its capacity to discern and differentiate nuances in emotional data for both valence and arousal classifications (H. Yang et al., 2019).

The intricacy of signals and the diverse array of pre-processing techniques and classifiers yield inconsistent outcomes in emotion recognition. Our study took a unique approach: transforming the features extracted from the flattened layer into fuzzy values using adjustable parameters and employing defuzzification. This method enriched the representational quality of the features, enhancing the model's recognition capacity significantly. Notably, our proposed technique outperformed recent studies by 6%-17%. Table 8 delineates a comparative analysis between our method and recent studies utilizing the same dataset, highlighting the superior performance of our approach.

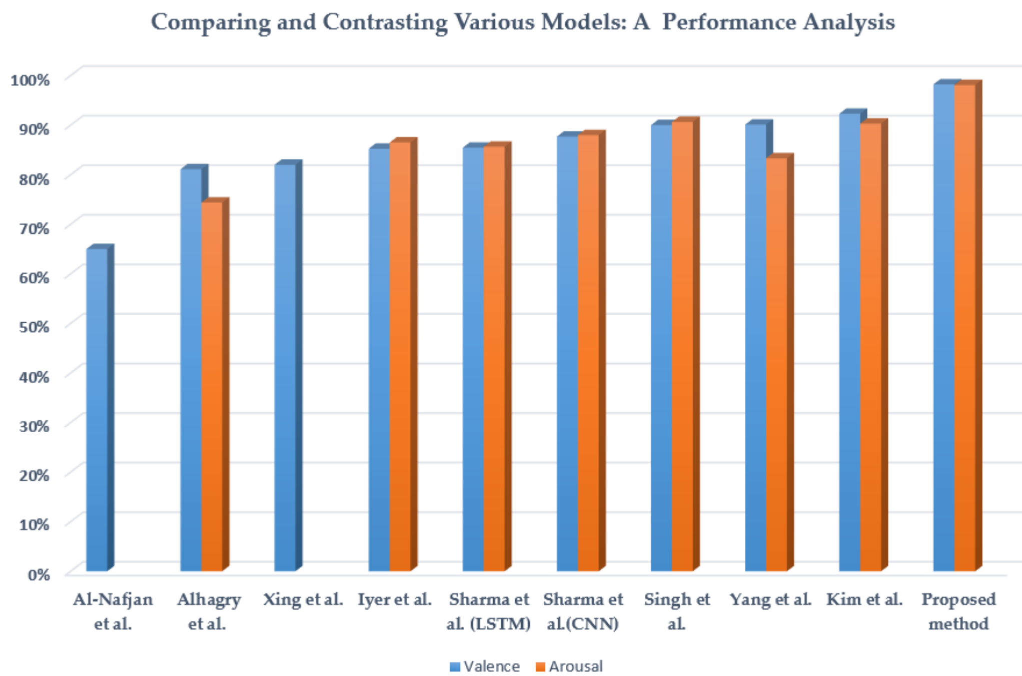
Table 8.

Comparison between our classification result and the findings of prior research.

Ref	Feature extraction domain	Classifier	Dataset	Results	
				Valence	Arousal
(Al-Nafjan et al., 2017)	PSD, Asymmetry features	DNN	DEAP	82%	82%
(Alhagry et al., 2017)	-	LSTM	DEAP	85.45%	85.65 %
(Xing et al., 2019)	Signal framing, Frequency band power, Pearson correlation	SAE+LSTM	DEAP	81.10%	74.38%
(Iyer et al., 2023)	Differential entropy	CNN+LSTM	DEAP-SEED	65% (DEAP)	
(Sharma & Meena, 2023)	PSD	CNN LSTM	DEAP-SEED	85.23% 87.68%	86.50% 87.98%
(K. Singh et al., 2023)	-	1D CNN+LSTM	DEAP	92.29%	90.33%
(H. Yang et al., 2019)	-	CNN	DEAP	90.01%	90.65%
(Y. Kim & Choi, 2020)	-	LSTM-Attention	DAEP	90.10%	83.30%
Author proposed	FFT	CFNN	DEAP	94.73%	94.08%

Figure 14.

Comparisons between our results with the results of previous models



CHAPTER VI

Conclusion and Recommendations

This chapter emphasizes the conclusions drawn from the study and further explores recommendations for future work.

Conclusion

Emotion embodies a comprehensive reflection of human feelings, thoughts, and behaviors, playing a crucial role in facilitating human communication between individuals. Emotion evaluation utilizes automatically differentiate various emotional states by utilizing signals, both physical and non-physical, obtained from humans. The goal is to facilitate efficient relationship and connection between humans and machines. Identifying and understanding emotions is crucial in human social interactions, mental health, education, and medical contexts. Understanding emotional states like happiness, sadness, fear, and love is fundamental to human existence, integral to our experiences and perceptions, and essential to our very conception of humanity. Remarkably, these very emotions, often considered intrinsic to human experience, can be accurately identified through brain signals obtained from EEG recordings.

False positives and the potential for image manipulation in image processing may compromise the result's accuracy. However, EEG brain wave signals, being inherently resistant to tampering, are immune to such alterations. This characteristic makes the process of recognizing and investigating emotions easier through the recording of brain signals. This study was employed to improve the precision of emotional identification derived from EEG signals by employing a combination of deep learning and fuzzy logic. The EEG signals underwent pre-processing to remove noise, feature extraction in the frequency domain through FFT, and classification conducted via an enhanced CFNN model.

A comparative analysis was conducted, employing four advanced, trained methods, indicating that the suggested approach surpassed other methods across all metrics. Furthermore, the model proposed in this study was compared with the latest research, demonstrating superior outcomes for the identical dataset. The proposed method achieved an impressive accuracy of

98.21% for valence and 98.08% for arousal. This exceptional performance highlights the significant impact of converting the extracted features into fuzzy representations after the convolutional layers, ultimately offering more detailed and insightful features during the recognition phase. The process of transforming these features into fuzzy representations following the convolutional layers significantly amplifies the quality of information available for accurate recognition and analysis of emotions.

Recommendation for future work

For future work, different deep learning models can be utilized to extract features and dynamically model data in multiclass, thereby enhancing overall performance. Moreover, leveraging a variety of features could lead to the adoption of more advanced fusion methods in future applications.

REFERENCES

Levenson, R. W. (1994). Human Emotions: A Functional View. In P. Ekman, & R .J. Davidson (Eds.), The Nature of Emotion: Fundamental Questions (pp. 123-126). New York, NY: Oxford University Press.Ackermann, P., Kohlschein, C., Bitsch, J. Á., Wehrle, K., & Jeschke, S. (2016). EEG-based automatic emotion recognition: Feature extraction, selection and classification methods. 2016 IEEE 18th International Conference on E-Health Networking, Applications and Services, Healthcom 2016. https://doi.org/10.1109/HealthCom.2016.7749447

Aftanas, L. I., & Golocheikine, S. A. (2002). Non-linear dynamic complexity of the human EEG during meditation. Neuroscience Letters, 330(2), 143–146. https://doi.org/10.1016/S0304-3940(02)00745-0

Akay, M., & Daubenspeck, J. A. (1999). Investigating the contamination of electroencephalograms by facial muscle electromyographic activity using matching pursuit. Brain and Language, 66(1), 184–200. https://doi.org/10.1006/brln.1998.2030

Akter, S., Prodhan, R. A., Pias, T. S., Eisenberg, D., & Fernandez, J. F. (2022). from Neural Activity.

Al-Nafjan, A., Hosny, M., Al-Wabil, A., & Al-Ohali, Y. (2017). Classification of Human Emotions from Electroencephalogram (EEG) Signal using Deep Neural Network. International Journal of Advanced Computer Science and Applications, 8(9), 419–425. https://doi.org/10.14569/ijacsa.2017.080955

Alarcão, S. M., & Fonseca, M. J. (2019). Emotions recognition using EEG signals: A survey. IEEE Transactions on Affective Computing, 10(3), 374–393. https://doi.org/10.1109/TAFFC.2017.2714671

Algarni, M., Saeed, F., Al-Hadhrami, T., Ghabban, F., & Al-Sarem, M. (2022). Deep Learning-Based Approach for Emotion Recognition Using Electroencephalography (EEG) Signals Using Bi-Directional Long Short-Term Memory (Bi-LSTM). Sensors, 22(8). https://doi.org/10.3390/s22082976

Alhagry, S., Aly, A., & A., R. (2017). Emotion Recognition based on EEG using LSTM Recurrent Neural Network. International Journal of Advanced Computer Science and Applications, 8(10), 8–11. https://doi.org/10.14569/ijacsa.2017.081046

Aljalal, M., Djemal, R., Alsharabi, K., & Ibrahim, S. (2018). Feature Extraction of EEG based

Motor Imagery Using CSP based on Logarithmic Band Power, Entropy and Energy. 1st International Conference on Computer Applications and Information Security, ICCAIS 2018, 1–6. https://doi.org/10.1109/CAIS.2018.8441995

Alotaiby, T., El-Samie, F. E. A., Alshebeili, S. A., & Ahmad, I. (2015). A review of channel selection algorithms for EEG signal processing. Eurasip Journal on Advances in Signal Processing, 2015(1). https://doi.org/10.1186/s13634-015-0251-9

Ansari-Asl, K., Chanel, G., & Pun, T. (2007). A channel selection method for EEG classification in emotion assessment based on synchronization likelihood. European Signal Processing Conference, January, 1241–1245.

Arjun, Rajpoot, A. S., & Panicker, M. R. (2022). Subject independent emotion recognition using EEG signals employing attention driven neural networks. Biomedical Signal Processing and Control, 75(September 2021), 103547. https://doi.org/10.1016/j.bspc.2022.103547

Bartels, G., Shi, L. C., & Lu, B. L. (2010). Automatic artifact removal from EEG - A mixed approach based on double blind source separation and support vector machine. 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10, 5383–5386. https://doi.org/10.1109/IEMBS.2010.5626481

Ben-Zeev, A. (1987). The nature of emotions. Philosophical Studies, 52(3), 393–409. https://doi.org/10.1007/BF00354055

Bista, S., & Adhikari, N. B. (2017). Design of Tri-channel Active Electrode EEG Device for Classification of Motor Imagery Brainwaves. 8914(July 2018), 57–66.

Choi, J. W., & Kim, K. H. (2018). Computational EEG Analysis. 125–145. https://doi.org/10.1007/978-981-13-0908-3

Cimtay, Y., & Ekmekcioglu, E. (2020). Investigating the use of pretrained convolutional neural network on cross-subject and cross-dataset eeg emotion recognition. Sensors (Switzerland), 20(7), 0–20. https://doi.org/10.3390/s20072034

Clynes, M. (1988). Generalised Emotion How it may be produced, and Sentic Cycle Therapy. Emotions and Psychopathology, 107–170. https://doi.org/10.1007/978-1-4757-1987-1_6

Dietrich, A., & Kanso, R. (2010). A review of EEG, ERP, and neuroimaging studies of creativity and insight. Psychological Bulletin, 136(5), 822–848. https://doi.org/10.1037/a0019749

Ekman, P., Friesen, W. V., O'Sullivan, M., Chan, A., Diacoyanni-Tarlatzis, I., Heider, K., Krause, R., LeCompte, W. A., Pitcairn, T., Ricci-Bitti, P. E., Scherer, K., Tomita, M., & Tzavaras, A.

(1987). Universals and Cultural Differences in the Judgments of Facial Expressions of Emotion. Journal of Personality and Social Psychology, 53(4), 712–717. https://doi.org/10.1037/0022-3514.53.4.712

Ekman, P., Friesen, W. V, Sullivan, M. O., Diacoyanni-tarlatzis, I., Krause, R., & Scherer, K. (1987). Universals and Cultural Differences in the Judgments of Facial Expressions PERSONALITY PROCESSES AND INDIVIDUAL Universals and Cultural Differences in the Judgments of Facial Expressions of Emotion. November. https://doi.org/10.1037/0022-3514.53.4.712

Ekman, P., & Friesen, W. (1978). Facial action coding system: A technique for the measurement of facial movement. Palo Alto. In Differences among unpleasant feelings. Motivation and Emotion.

Emotions, H. (1978). Human emotion. In Nebraska Symposium on Motivation. Nebraska Symposium on Motivation (Vol. 26). https://doi.org/10.2307/j.ctv1s5nz6h.91

Estepp, J. R., Klosterman, S. L., & Christensen, J. C. (2011). An assessment of non-stationarity in physiological cognitive state assessment using artificial neural networks. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 6552–6555. https://doi.org/10.1109/IEMBS.2011.6091616

Frackowiak, R. S. J. (2017). The functional architecture of the brain. The Brain, 127(2), 105–130. https://doi.org/10.4324/9781351305204-4

Gai, J., & Hu, Y. (2018). Research on Fault Diagnosis Based on Singular Value Decomposition and Fuzzy Neural Network. Shock and Vibration, 2018. https://doi.org/10.1155/2018/8218657

Gao, Z., Wang, X., Yang, Y., Li, Y., Ma, K., & Chen, G. (2020). A Channel-fused Dense Convolutional Network for EEG-based Emotion Recognition. IEEE Transactions on Cognitive and Developmental Systems, 8920(c), 1–1. https://doi.org/10.1109/tcds.2020.2976112

Garg, A., Kapoor, A., Bedi, A. K., & Sunkaria, R. K. (2019). Merged LSTM Model for emotion classification using EEG signals. 2019 International Conference on Data Science and Engineering, ICDSE 2019, 139–143. https://doi.org/10.1109/ICDSE47409.2019.8971484

Garrett, D., Peterson, D. A., Anderson, C. W., & Thaut, M. H. (2003). X k 1 N k = N k Z = f (T X) O = f (T Z). 11(2), 141–144.

Gath, I., & Geva, A. B. (1989). Unsupervised Optimal Fuzzy Clustering. IEEE Transactions on Pattern Analysis and Machine Intelligence, 11(7), 773–780. https://doi.org/10.1109/34.192473

Gliner, J. A., Morgan, G. A., Leech, N. L., Gliner, J. A., & Morgan, G. A. (2021). Measurement Reliability and Validity. Research Methods in Applied Settings, 319–338. https://doi.org/10.4324/9781410605337-29

Gnana, D. A. A. (2016). Literature Review on Feature Selection Methods for High-Dimensional Data Literature Review on Feature Selection Methods for High-Dimensional Data. February. https://doi.org/10.5120/ijca2016908317

Gratton, G., Coles, M. G. H., & Donchin, E. (1983). A new method for off-line removal of ocular artifact. Electroencephalography and Clinical Neurophysiology, 55(4), 468–484. https://doi.org/10.1016/0013-4694(83)90135-9

Green, C. D. (1912). Livros Grátis. 1.

Healey, J. A., Picard, R. W., Smith, A. C., & Healey, J. A. (2000). Wearable and Automotive Systems for Affect Recognition from Physiology by Certified by .... Wearable and Automotive Systems for Affect Recognition by. 158.

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Iyer, A., Das, S. S., Teotia, R., Maheshwari, S., & Sharma, R. R. (2022). CNN and LSTM based ensemble learning for human emotion recognition using EEG recordings. Multimedia Tools and Applications. https://doi.org/10.1007/s11042-022-12310-7

Iyer, A., Das, S. S., Teotia, R., Maheshwari, S., & Sharma, R. R. (2023). CNN and LSTM based ensemble learning for human emotion recognition using EEG recordings. Multimedia Tools and Applications, 82(4), 4883–4896. https://doi.org/10.1007/s11042-022-12310-7

Izard, C., Fine, S., Schultz, D., Mostow, A., Ackerman, B., & Youngstrom, E. (2001). Emotion knowledge as a predictor of social behavior and academic competence in children at risk. Psychological Science, 12(1), 18–23. https://doi.org/10.1111/1467-9280.00304

James, W. (1884). Mind Association What is an Emotion ? Author (s): William James Published by : Oxford University Press on behalf of the Mind Association Stable URL : http://www.jstor.org/stable/2246769 Accessed : 30-03-2016 19 : 58 UTC Your use of the JSTOR archive ind. 9(34), 188–205.

Jaušovec, N., Jaušovec, K., & Gerlič, I. (2001). Differences in event-related and induced EEG patterns in the theta and alpha frequency bands related to human emotional intelligence. Neuroscience Letters, 311(2), 93–96. https://doi.org/10.1016/S0304-3940(01)02141-3

Jenke, R., Peer, A., & Buss, M. (2014). Feature extraction and selection for emotion recognition from EEG. IEEE Transactions on Affective Computing, 5(3), 327–339. https://doi.org/10.1109/TAFFC.2014.2339834

Ketter, P. (2010). How the brain learns···. In T and D (Vol. 64, Issue 5). https://doi.org/10.4135/9781071855324

Kim, M. K., Kim, M., Oh, E., & Kim, S. P. (2013). A review on the computational methods for emotional state estimation from the human EEG. Computational and Mathematical Methods in Medicine, 2013. https://doi.org/10.1155/2013/573734

Kim, Y., & Choi, A. (2020). Eeg-based emotion classification using long short-term memory network with attention mechanism. Sensors (Switzerland), 20(23), 1–22. https://doi.org/10.3390/s20236727

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a rKlimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain Research Reviews, 29(2-3), 169–195. doi:10.1016/S016. Brain Research Reviews, 29(2–3), 169–195. https://doi.org/10.1016/S0165-0173(98)00056-3

Koelstra, S., Member, S., Member, S., Lee, J., Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A., & Patras, I. (n.d.). DEAP : A Database for Emotion Analysis using Physiological Signals. 1–15.

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (1997). International affective picture system (IAPS): Technical manual and affective ratings. NIMH Center for the Study of Emotion and Attention, 39–58.

Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539

Li, Mi, Xu, H., Liu, X., & Lu, S. (2018). Emotion recognition from multichannel EEG signals using K-nearest neighbor classification. Technology and Health Care, 26(S1), S509–S519. https://doi.org/10.3233/THC-174836

Li, Mu, & Member, B. L. S. (2009). 05334139.Pdf. Ieeexplore.Ieee.Org, 1323–1326. https://ieeexplore.ieee.org/abstract/document/5334139/

Liu, H., Zhang, Y., Li, Y., & Kong, X. (2021). Review on Emotion Recognition Based on Electroencephalography. Frontiers in Computational Neuroscience, 15(October), 1–15. https://doi.org/10.3389/fncom.2021.758212

Liu, J., Meng, H., Nandi, A., & Li, M. (2016). Emotion detection from EEG recordings. 2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery, ICNC-FSKD 2016, 1722–1727. https://doi.org/10.1109/FSKD.2016.7603437

Liu, Y., & Fu, G. (2021). Emotion recognition by deeply learned multi-channel textual and EEG features. Future Generation Computer Systems, 119, 1–6. https://doi.org/10.1016/j.future.2021.01.010

Mahajan, R., & Morshed, B. I. (2015). Unsupervised eye blink artifact denoising of EEG data with modified multiscale sample entropy, kurtosis, and wavelet-ICA. IEEE Journal of Biomedical and Health Informatics, 19(1), 158–165. https://doi.org/10.1109/JBHI.2014.2333010

Mehrabian, A. (1996). Pleasure-Arousal-Dominance: A general framework for describing and measuring individual differences in temperament. Current Psychology, 14(4), 261–292. https://doi.org/10.1007/bf02686918

Mohammadi, Z., Frounchi, J., & Amiri, M. (2017). Wavelet-based emotion recognition system using EEG signal. Neural Computing and Applications, 28(8), 1985–1990. https://doi.org/10.1007/s00521-015-2149-8

Moon, Seong-Eun, Jang Soobeom, L. J.-S. (2018). CONVOLUTIONAL NEURAL NETWORK APPROACH FOR EEG-BASED EMOTION RECOGNITION USING BRAIN CONNECTIVITY AND ITS SPATIAL INFORMATION Seong-Eun Moon Soobeom Jang Jong-Seok Lee Republic of Korea. 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2556–2560.

Mukrimaa, S. S., Nurdyansyah, Fahyuni, E. F., YULIA CITRA, A., Schulz, N. D., غسان, د., Taniredja, T., Faridli, E. M., & Harmianto, S. (2016). No 主観的健康感を中心とした在宅高齢者における　健康関連指標に関する共分散構造分析Title. In Jurnal Penelitian Pendidikan Guru Sekolah Dasar (Vol. 6, Issue August).

Murugappan, M. (2013). Human Emotion Recognition Through Short Time Electroencephalogram (EEG) Signals Using Fast Fourier Transform (FFT). 8–10.

Nakisa, B., Rastgoo, M. N., Rakotonirainy, A., Maire, F., & Chandran, V. (2018). Long short term memory hyperparameter optimization for a neural network based emotion recognition framework. IEEE Access, 6, 49325–49338. https://doi.org/10.1109/ACCESS.2018.2868361

Nandini, D., Yadav, J., Rani, A., & Singh, V. (2023). Biomedical Signal Processing and Control Design of subject independent 3D VAD emotion detection system using EEG signals and machine learning algorithms. Biomedical Signal Processing and Control, 85(March), 104894. https://doi.org/10.1016/j.bspc.2023.104894

Ozdemir, M. A., Degirmenci, M., Izci, E., & Akan, A. (2021). EEG-based emotion recognition with deep convolutional neural networks. Biomedizinische Technik, 66(1), 43–57. https://doi.org/10.1515/bmt-2019-0306

Pedrycz, W., & Gomide, F. (2007). Fuzzy Systems Engineering Computing. In Systems Research. http://www.wiley.com/go/p

Pramudita, B. A., Nugroho, Y. D., Ardiyanto, I., Shapiai, M. I., & Setiawan, N. A. (2018). Removing ocular artefacts in EEG signals by using combination of complete EEMD (CEEMD) - Independent Component Analysis (ICA) based outlier data. Proceeding of 2017 International Conference on Robotics, Automation and Sciences, ICORAS 2017, 2018-March, 1–5. https://doi.org/10.1109/ICORAS.2017.8308056

Press, I. (1927). The James-Lange Theory of Emotions : A Critical Examination and an Alternative Theory Author (s): Walter B . Cannon Published by : University of Illinois Press Stable URL : https://www.jstor.org/stable/1415404 REFERENCES Linked references are available . 39(1), 106–124.

Ramzan, M., & Dawn, S. (2021). Fused CNN-LSTM deep learning emotion recognition model using electroencephalography signals. International Journal of Neuroscience, 0(0), 000. https://doi.org/10.1080/00207454.2021.1941947

Rao, R., & Derakhshani, R. (2005). A comparison of EEG preprocessing methods using time delay neural networks. 2nd International IEEE EMBS Conference on Neural Engineering, 2005, 262–264. https://doi.org/10.1109/CNE.2005.1419607

Ren, Y., & Wu, Y. (2014). Convolutional deep belief networks for feature extraction of EEG signal. Proceedings of the International Joint Conference on Neural Networks, 2850–2853. https://doi.org/10.1109/IJCNN.2014.6889383

Romand, A. (2004). Sharing the power. PEI Power Engineering International, 12(4), 34.

Ruck, D. W., Rogers, S. K., Kabrisky, M., Oxley, M. E., & Suter, B. W. (1990). Letters: The Multilayer Perceptron as an Approximation to a Bayes Optimal Discriminant Function. IEEE

Transactions on Neural Networks, 1(4), 296–298. https://doi.org/10.1109/72.80266

Santillan-Guzman, A., Oliveros-Oliveros, J. J., & Morin-Castillo, M. M. (2018). Introducing a Combination of ICA-EMD to Suppress Muscle and Ocular Artifacts in EEG Signals. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2018-July, 1250–1253. https://doi.org/10.1109/EMBC.2018.8512581

Sarma, P., & Barma, S. (2021). Emotion recognition by distinguishing appropriate EEG segments based on random matrix theory. Biomedical Signal Processing and Control, 70(July), 102991. https://doi.org/10.1016/j.bspc.2021.102991

Satuluri, D., Saiteja, B., Milinda, S. K., & Singh, P. (2022). Study of EEG based Emotion Classification using Convolutional Neural Networks. 2022 8th International Conference on Signal Processing and Communication, ICSC 2022, 508–513. https://doi.org/10.1109/ICSC56524.2022.10009458

Sharma, R., & Meena, H. K. (2023). EmHM: A Novel Hybrid Model for the Emotion Recognition based on EEG Signals. 2023 19th IEEE International Colloquium on Signal Processing and Its Applications, CSPA 2023 - Conference Proceedings, March, 75–80. https://doi.org/10.1109/CSPA57446.2023.10087500

Singh, R. K., & Singh, P. A. K. (2014). Frequency Analysis of Healthy & Epileptic Seizure in EEG using Fast Fourier Transform. 2(4), 683–691.

Song, T., Zheng, W., Song, P., & Cui, Z. (2020). EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks. IEEE Transactions on Affective Computing, 11(3), 532–541. https://doi.org/10.1109/TAFFC.2018.2817622

Sourina, O., & Liu, Y. (2011). A fractal-based algorithm of emotion recognition from EEG using arousal-valence model. BIOSIGNALS 2011 - Proceedings of the International Conference on Bio-Inspired Systems and Signal Processing, 209–214. https://doi.org/10.5220/0003151802090214

Srivastava, G., Crottaz-Herbette, S., Lau, K. M., Glover, G. H., & Menon, V. (2005). ICA-based procedures for removing ballistocardiogram artifacts from EEG data acquired in the MRI scanner. NeuroImage, 24(1), 50–60. https://doi.org/10.1016/j.neuroimage.2004.09.041

Subasi, A., & Gursoy, M. I. (2010). EEG signal classification using PCA, ICA, LDA and support vector machines. Expert Systems with Applications, 37(12), 8659–8666.

https://doi.org/10.1016/j.eswa.2010.06.065

Subha, D. P., Joseph, P. K., Acharya U, R., & Lim, C. M. (2010). EEG signal analysis: a survey. Journal of Medical Systems, 34(2), 195–212. https://doi.org/10.1007/s10916-008-9231-z

Tao, W., Li, C., Song, R., Cheng, J., Liu, Y., Wan, F., & Chen, X. (2020). EEG-based Emotion Recognition via Channel-wise Attention and Self Attention. IEEE Transactions on Affective Computing, 3045(c), 1–12. https://doi.org/10.1109/TAFFC.2020.3025777

Transactions, W., Processing, S., & Lumpur, K. (2016). Asymmetric ratio and FCM based salient channel selection for human emotion detection using Article in WSEAS Transactions on Signal Processing · January 2008 Asymmetric Ratio and FCM based Salient Channel Selection for. January 2008.

Trier, H. (2012). Fordele ved at strukturere mundtlig kommunikation. Ugeskrift for Laeger, 174(26), 1796.

Vinther, M. (2002). Independent Component Analysis of Evoked Potentials in EEG. 1–23.

Wagh, K. P., & Vasanth, K. (2019). Electroencephalograph (EEG) Based Emotion Recognition System: A Review. In Lecture Notes in Networks and Systems (Vol. 33). Springer Singapore. https://doi.org/10.1007/978-981-10-8204-7_5

Wallstrom, G. L., Kass, R. E., Miller, A., Cohn, J. F., & Fox, N. A. (2004). Automatic correction of ocular artifacts in the EEG: A comparison of regression-based and component-based methods. International Journal of Psychophysiology, 53(2), 105–119. https://doi.org/10.1016/j.ijpsycho.2004.03.007

Wang, X. W., Nie, D., & Lu, B. L. (2011). EEG-based emotion recognition using frequency domain features and support vector machines. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7062 LNCS(PART 1), 734–743. https://doi.org/10.1007/978-3-642-24955-6_87

Xiao, G., Shi, M., Ye, M., Xu, B., Chen, Z., & Ren, Q. (2022). 4D attention-based neural network for EEG emotion recognition. Cognitive Neurodynamics, 16(4), 805–818. https://doi.org/10.1007/s11571-021-09751-5

Xing, X., Li, Z., Xu, T., Shu, L., Hu, B., & Xu, X. (2019). SAE+LSTM: A new framework for emotion recognition from multi-channel EEG. Frontiers in Neurorobotics, 13(June), 1–14. https://doi.org/10.3389/fnbot.2019.00037

Xu, H. (2012). Towards Automated Recognition of Human Emotions using by A thesis submitted in conformity with the requirements Graduate Department of Electrical and Computer Engineering Abstract. 1–155.

Yanagimoto, M., & Sugimoto, C. (2016). Convolutional neural networks using supervised pre-training for EEG-based emotion recognition. Proceedings of the International Workshop on Biosignal Interpretation, November 2016, 72–75.

Yang, H., Han, J., & Min, K. (2019). A multi-column CNN model for emotion recognition from EEG signals. Sensors (Switzerland), 19(21), 1–12. https://doi.org/10.3390/s19214736

Yang, S., & Deravi, F. (2013). Wavelet-based EEG preprocessing for biometric applications. Proceedings - 2013 4th International Conference on Emerging Security Technologies, EST 2013, 43–46. https://doi.org/10.1109/EST.2013.14

Yin, Y., Zheng, X., Hu, B., Zhang, Y., & Cui, X. (2021). EEG emotion recognition using fusion model of graph convolutional neural networks and LSTM. Applied Soft Computing, 100, 106954. https://doi.org/10.1016/j.asoc.2020.106954

Zadeh, L. A. (1994). Fuzzy Logic, Neural Networks, and Soft Computing. Communications of the ACM, 37(3), 77–84. https://doi.org/10.1145/175247.175255

Zali-Vargahan, B., Charmin, A., Kalbkhani, H., & Barghandan, S. (2023). Deep time-frequency features and semi-supervised dimension reduction for subject-independent emotion recognition from multi-channel EEG signals. Biomedical Signal Processing and Control, 85(August 2022), 104806. https://doi.org/10.1016/j.bspc.2023.104806

Zamani, F., & Wulansari, R. (2021). Emotion Classification using 1D-CNN and RNN based On DEAP Dataset. 363–378. https://doi.org/10.5121/csit.2021.112328

Zhang, Jianhai, Chen, M., Zhao, S., Hu, S., Shi, Z., & Cao, Y. (2016). ReliefF-based EEG sensor selection methods for emotion recognition. Sensors (Switzerland), 16(10), 1–15. https://doi.org/10.3390/s16101558

Zhang, Jianhua, Yin, Z., Chen, P., & Nichele, S. (2020). Emotion recognition using multi-modal data and machine learning techniques : A tutorial and review. Information Fusion, 59(March 2019), 103–126. https://doi.org/10.1016/j.inffus.2020.01.011

Zheng, W. L., & Lu, B. L. (2015). Investigating Critical Frequency Bands and Channels for EEG-Based Emotion Recognition with Deep Neural Networks. IEEE Transactions on Autonomous Mental Development, 7(3), 162–175. https://doi.org/10.1109/TAMD.2015.2431497

Zheng, W., Member, S., Lu, B., & Member, S. (2015). Investigating Critical Frequency Bands and

Channels for EEG-based Emotion Recognition with Deep Neural Networks. 0604(c), 1–14. https://doi.org/10.1109/TAMD.2015.2431497

Zhou, Wcidong. (2002). ECG Artifacts from EEG Using ICA. Electronics, 206–207.

Zhou, Weidong, & Gotman, J. (2009). Automatic removal of eye movement artifacts from the EEG using ICA and the dipole model. Progress in Natural Science, 19(9), 1165–1170. https://doi.org/10.1016/j.pnsc.2008.11.013

Zima, M., Tichavsk, P., Paul, K., & Krajča, V. (2012). Robust removal of short-duration artifacts in long neonatal EEG recordings using wavelet-enhanced ICA and adaptive combining of tentative reconstructions. Physiological Measurement, 33(8). https://doi.org/10.1088/0967-3334/33/8/N39

Zouridakis, G., Patidar, U., Padhye, N. S., Pollonini, L., Passaro, A., & Papanicolaou, A. C. (2010). Spectral power of brain activity associated with emotion - A pilot MEG study. IFMBE Proceedings, 28, 354–357. https://doi.org/10.1007/978-3-642-12197-5_83

46-Human Emotion94.pdf. (n.d.).

Ackermann, P., Kohlschein, C., Bitsch, J. Á., Wehrle, K., & Jeschke, S. (2016). EEG-based automatic emotion recognition: Feature extraction, selection and classification methods. 2016 IEEE 18th International Conference on E-Health Networking, Applications and Services, Healthcom 2016. https://doi.org/10.1109/HealthCom.2016.7749447

Aftanas, L. I., & Golocheikine, S. A. (2002). Non-linear dynamic complexity of the human EEG during meditation. Neuroscience Letters, 330(2), 143–146. https://doi.org/10.1016/S0304-3940(02)00745-0

Akay, M., & Daubenspeck, J. A. (1999). Investigating the contamination of electroencephalograms by facial muscle electromyographic activity using matching pursuit. Brain and Language, 66(1), 184–200. https://doi.org/10.1006/brln.1998.2030

Akter, S., Prodhan, R. A., Pias, T. S., Eisenberg, D., & Fernandez, J. F. (2022). from Neural Activity.

Al-Nafjan, A., Hosny, M., Al-Wabil, A., & Al-Ohali, Y. (2017). Classification of Human Emotions from Electroencephalogram (EEG) Signal using Deep Neural Network. International Journal of Advanced Computer Science and Applications, 8(9), 419–425. https://doi.org/10.14569/ijacsa.2017.080955

Alarcão, S. M., & Fonseca, M. J. (2019). Emotions recognition using EEG signals: A survey. IEEE

Transactions on Affective Computing, 10(3), 374–393. https://doi.org/10.1109/TAFFC.2017.2714671

Algarni, M., Saeed, F., Al-Hadhrami, T., Ghabban, F., & Al-Sarem, M. (2022). Deep Learning-Based Approach for Emotion Recognition Using Electroencephalography (EEG) Signals Using Bi-Directional Long Short-Term Memory (Bi-LSTM). Sensors, 22(8). https://doi.org/10.3390/s22082976

Alhagry, S., Aly, A., & A., R. (2017). Emotion Recognition based on EEG using LSTM Recurrent Neural Network. International Journal of Advanced Computer Science and Applications, 8(10), 8–11. https://doi.org/10.14569/ijacsa.2017.081046

Aljalal, M., Djemal, R., Alsharabi, K., & Ibrahim, S. (2018). Feature Extraction of EEG based Motor Imagery Using CSP based on Logarithmic Band Power, Entropy and Energy. 1st International Conference on Computer Applications and Information Security, ICCAIS 2018, 1–6. https://doi.org/10.1109/CAIS.2018.8441995

Alotaiby, T., El-Samie, F. E. A., Alshebeili, S. A., & Ahmad, I. (2015). A review of channel selection algorithms for EEG signal processing. Eurasip Journal on Advances in Signal Processing, 2015(1). https://doi.org/10.1186/s13634-015-0251-9

Ansari-Asl, K., Chanel, G., & Pun, T. (2007). A channel selection method for EEG classification in emotion assessment based on synchronization likelihood. European Signal Processing Conference, January, 1241–1245.

Arjun, Rajpoot, A. S., & Panicker, M. R. (2022). Subject independent emotion recognition using EEG signals employing attention driven neural networks. Biomedical Signal Processing and Control, 75(September 2021), 103547. https://doi.org/10.1016/j.bspc.2022.103547

Bartels, G., Shi, L. C., & Lu, B. L. (2010). Automatic artifact removal from EEG - A mixed approach based on double blind source separation and support vector machine. 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10, 5383–5386. https://doi.org/10.1109/IEMBS.2010.5626481

Ben-Zeev, A. (1987). The nature of emotions. Philosophical Studies, 52(3), 393–409. https://doi.org/10.1007/BF00354055

Bista, S., & Adhikari, N. B. (2017). Design of Tri-channel Active Electrode EEG Device for Classification of Motor Imagery Brainwaves. 8914(July 2018), 57–66.

Choi, J. W., & Kim, K. H. (2018). Computational EEG Analysis. 125–145.

https://doi.org/10.1007/978-981-13-0908-3

Cimtay, Y., & Ekmekcioglu, E. (2020). Investigating the use of pretrained convolutional neural network on cross-subject and cross-dataset eeg emotion recognition. Sensors (Switzerland), 20(7), 0–20. https://doi.org/10.3390/s20072034

Clynes, M. (1988). Generalised Emotion How it may be produced, and Sentic Cycle Therapy. Emotions and Psychopathology, 107–170. https://doi.org/10.1007/978-1-4757-1987-1_6

Dietrich, A., & Kanso, R. (2010). A review of EEG, ERP, and neuroimaging studies of creativity and insight. Psychological Bulletin, 136(5), 822–848. https://doi.org/10.1037/a0019749

Ekman, P., Friesen, W. V., O'Sullivan, M., Chan, A., Diacoyanni-Tarlatzis, I., Heider, K., Krause, R., LeCompte, W. A., Pitcairn, T., Ricci-Bitti, P. E., Scherer, K., Tomita, M., & Tzavaras, A. (1987). Universals and Cultural Differences in the Judgments of Facial Expressions of Emotion. Journal of Personality and Social Psychology, 53(4), 712–717. https://doi.org/10.1037/0022-3514.53.4.712

Ekman, P., Friesen, W. V, Sullivan, M. O., Diacoyanni-tarlatzis, I., Krause, R., & Scherer, K. (1987). Universals and Cultural Differences in the Judgments of Facial Expressions PERSONALITY PROCESSES AND INDIVIDUAL Universals and Cultural Differences in the Judgments of Facial Expressions of Emotion. November. https://doi.org/10.1037/0022-3514.53.4.712

Ekman, P., & Friesen, W. (1978). Facial action coding system: A technique for the measurement of facial movement. Palo Alto. In Differences among unpleasant feelings. Motivation and Emotion.

Emotions, H. (1978). Human emotion. In Nebraska Symposium on Motivation. Nebraska Symposium on Motivation (Vol. 26). https://doi.org/10.2307/j.ctv1s5nz6h.91

Estepp, J. R., Klosterman, S. L., & Christensen, J. C. (2011). An assessment of non-stationarity in physiological cognitive state assessment using artificial neural networks. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 6552–6555. https://doi.org/10.1109/IEMBS.2011.6091616

Frackowiak, R. S. J. (2017). The functional architecture of the brain. The Brain, 127(2), 105–130. https://doi.org/10.4324/9781351305204-4

Gai, J., & Hu, Y. (2018). Research on Fault Diagnosis Based on Singular Value Decomposition and Fuzzy Neural Network. Shock and Vibration, 2018.

https://doi.org/10.1155/2018/8218657

Gao, Z., Wang, X., Yang, Y., Li, Y., Ma, K., & Chen, G. (2020). A Channel-fused Dense Convolutional Network for EEG-based Emotion Recognition. IEEE Transactions on Cognitive and Developmental Systems, 8920(c), 1–1. https://doi.org/10.1109/tcds.2020.2976112

Garg, A., Kapoor, A., Bedi, A. K., & Sunkaria, R. K. (2019). Merged LSTM Model for emotion classification using EEG signals. 2019 International Conference on Data Science and Engineering, ICDSE 2019, 139–143. https://doi.org/10.1109/ICDSE47409.2019.8971484

Garrett, D., Peterson, D. A., Anderson, C. W., & Thaut, M. H. (2003). X k 1 N k = N k Z = f (T X) O = f (T Z). 11(2), 141–144.

Gath, I., & Geva, A. B. (1989). Unsupervised Optimal Fuzzy Clustering. IEEE Transactions on Pattern Analysis and Machine Intelligence, 11(7), 773–780. https://doi.org/10.1109/34.192473

Gliner, J. A., Morgan, G. A., Leech, N. L., Gliner, J. A., & Morgan, G. A. (2021). Measurement Reliability and Validity. Research Methods in Applied Settings, 319–338. https://doi.org/10.4324/9781410605337-29

Gnana, D. A. A. (2016). Literature Review on Feature Selection Methods for High-Dimensional Data Literature Review on Feature Selection Methods for High-Dimensional Data. February. https://doi.org/10.5120/ijca2016908317

Gratton, G., Coles, M. G. H., & Donchin, E. (1983). A new method for off-line removal of ocular artifact. Electroencephalography and Clinical Neurophysiology, 55(4), 468–484. https://doi.org/10.1016/0013-4694(83)90135-9

Green, C. D. (1912). Livros Grátis. 1.

Healey, J. A., Picard, R. W., Smith, A. C., & Healey, J. A. (2000). Wearable and Automotive Systems for Affect Recognition from Physiology by Certified by .... Wearable and Automotive Systems for Affect Recognition by. 158.

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Iyer, A., Das, S. S., Teotia, R., Maheshwari, S., & Sharma, R. R. (2022). CNN and LSTM based ensemble learning for human emotion recognition using EEG recordings. Multimedia Tools and Applications. https://doi.org/10.1007/s11042-022-12310-7

Iyer, A., Das, S. S., Teotia, R., Maheshwari, S., & Sharma, R. R. (2023). CNN and LSTM based ensemble learning for human emotion recognition using EEG recordings. Multimedia Tools and Applications, 82(4), 4883–4896. https://doi.org/10.1007/s11042-022-12310-7

Izard, C., Fine, S., Schultz, D., Mostow, A., Ackerman, B., & Youngstrom, E. (2001). Emotion knowledge as a predictor of social behavior and academic competence in children at risk. Psychological Science, 12(1), 18–23. https://doi.org/10.1111/1467-9280.00304

James, W. (1884). Mind Association What is an Emotion ? Author (s): William James Published by : Oxford University Press on behalf of the Mind Association Stable URL : http://www.jstor.org/stable/2246769 Accessed : 30-03-2016 19 : 58 UTC Your use of the JSTOR archive ind. 9(34), 188–205.

Jaušovec, N., Jaušovec, K., & Gerlič, I. (2001). Differences in event-related and induced EEG patterns in the theta and alpha frequency bands related to human emotional intelligence. Neuroscience Letters, 311(2), 93–96. https://doi.org/10.1016/S0304-3940(01)02141-3

Jenke, R., Peer, A., & Buss, M. (2014). Feature extraction and selection for emotion recognition from EEG. IEEE Transactions on Affective Computing, 5(3), 327–339. https://doi.org/10.1109/TAFFC.2014.2339834

Ketter, P. (2010). How the brain learns···. In T and D (Vol. 64, Issue 5). https://doi.org/10.4135/9781071855324

Kim, M. K., Kim, M., Oh, E., & Kim, S. P. (2013). A review on the computational methods for emotional state estimation from the human EEG. Computational and Mathematical Methods in Medicine, 2013. https://doi.org/10.1155/2013/573734

Kim, Y., & Choi, A. (2020). Eeg-based emotion classification using long short-term memory network with attention mechanism. Sensors (Switzerland), 20(23), 1–22. https://doi.org/10.3390/s20236727

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a rKlimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain Research Reviews, 29(2-3), 169–195. doi:10.1016/S016. Brain Research Reviews, 29(2–3), 169–195. https://doi.org/10.1016/S0165-0173(98)00056-3

Koelstra, S., Member, S., Member, S., Lee, J., Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A., & Patras, I. (n.d.). DEAP : A Database for Emotion Analysis using Physiological Signals. 1–15.

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (1997). International affective picture system (IAPS): Technical manual and affective ratings. NIMH Center for the Study of Emotion and Attention, 39–58.

Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539

Li, Mi, Xu, H., Liu, X., & Lu, S. (2018). Emotion recognition from multichannel EEG signals using K-nearest neighbor classification. Technology and Health Care, 26(S1), S509–S519. https://doi.org/10.3233/THC-174836

Li, Mu, & Member, B. L. S. (2009). 05334139.Pdf. Ieeexplore.Ieee.Org, 1323–1326. https://ieeexplore.ieee.org/abstract/document/5334139/

Liu, H., Zhang, Y., Li, Y., & Kong, X. (2021). Review on Emotion Recognition Based on Electroencephalography. Frontiers in Computational Neuroscience, 15(October), 1–15. https://doi.org/10.3389/fncom.2021.758212

Liu, J., Meng, H., Nandi, A., & Li, M. (2016). Emotion detection from EEG recordings. 2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery, ICNC-FSKD 2016, 1722–1727. https://doi.org/10.1109/FSKD.2016.7603437

Liu, Y., & Fu, G. (2021). Emotion recognition by deeply learned multi-channel textual and EEG features. Future Generation Computer Systems, 119, 1–6. https://doi.org/10.1016/j.future.2021.01.010

Mahajan, R., & Morshed, B. I. (2015). Unsupervised eye blink artifact denoising of EEG data with modified multiscale sample entropy, kurtosis, and wavelet-ICA. IEEE Journal of Biomedical and Health Informatics, 19(1), 158–165. https://doi.org/10.1109/JBHI.2014.2333010

Mehrabian, A. (1996). Pleasure-Arousal-Dominance: A general framework for describing and measuring individual differences in temperament. Current Psychology, 14(4), 261–292. https://doi.org/10.1007/bf02686918

Mohammadi, Z., Frounchi, J., & Amiri, M. (2017). Wavelet-based emotion recognition system using EEG signal. Neural Computing and Applications, 28(8), 1985–1990. https://doi.org/10.1007/s00521-015-2149-8

Moon, Seong-Eun, Jang Soobeom, L. J.-S. (2018). CONVOLUTIONAL NEURAL NETWORK APPROACH FOR EEG-BASED EMOTION RECOGNITION USING BRAIN CONNECTIVITY AND ITS SPATIAL INFORMATION Seong-Eun Moon Soobeom Jang

Jong-Seok Lee Republic of Korea. 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2556–2560.

Mukrimaa, S. S., Nurdyansyah, Fahyuni, E. F., YULIA CITRA, A., Schulz, N. D., غسان, د., Taniredja, T., Faridli, E. M., & Harmianto, S. (2016). No 主観的健康感を中心とした在宅高齢者における　健康関連指標に関する共分散構造分析Title. In Jurnal Penelitian Pendidikan Guru Sekolah Dasar (Vol. 6, Issue August).

Murugappan, M. (2013). Human Emotion Recognition Through Short Time Electroencephalogram (EEG) Signals Using Fast Fourier Transform (FFT). 8–10.

Nakisa, B., Rastgoo, M. N., Rakotonirainy, A., Maire, F., & Chandran, V. (2018). Long short term memory hyperparameter optimization for a neural network based emotion recognition framework. IEEE Access, 6, 49325–49338. https://doi.org/10.1109/ACCESS.2018.2868361

Nandini, D., Yadav, J., Rani, A., & Singh, V. (2023). Biomedical Signal Processing and Control Design of subject independent 3D VAD emotion detection system using EEG signals and machine learning algorithms. Biomedical Signal Processing and Control, 85(March), 104894. https://doi.org/10.1016/j.bspc.2023.104894

Ozdemir, M. A., Degirmenci, M., Izci, E., & Akan, A. (2021). EEG-based emotion recognition with deep convolutional neural networks. Biomedizinische Technik, 66(1), 43–57. https://doi.org/10.1515/bmt-2019-0306

Pedrycz, W., & Gomide, F. (2007). Fuzzy Systems Engineering Computing. In Systems Research. http://www.wiley.com/go/p

Pramudita, B. A., Nugroho, Y. D., Ardiyanto, I., Shapiai, M. I., & Setiawan, N. A. (2018). Removing ocular artefacts in EEG signals by using combination of complete EEMD (CEEMD) - Independent Component Analysis (ICA) based outlier data. Proceeding of 2017 International Conference on Robotics, Automation and Sciences, ICORAS 2017, 2018-March, 1–5. https://doi.org/10.1109/ICORAS.2017.8308056

Press, I. (1927). The James-Lange Theory of Emotions : A Critical Examination and an Alternative Theory Author (s): Walter B . Cannon Published by : University of Illinois Press Stable URL : https://www.jstor.org/stable/1415404 REFERENCES Linked references are available . 39(1), 106–124.

Ramzan, M., & Dawn, S. (2021). Fused CNN-LSTM deep learning emotion recognition model using electroencephalography signals. International Journal of Neuroscience, 0(0), 000.

https://doi.org/10.1080/00207454.2021.1941947

Rao, R., & Derakhshani, R. (2005). A comparison of EEG preprocessing methods using time delay neural networks. 2nd International IEEE EMBS Conference on Neural Engineering, 2005, 262–264. https://doi.org/10.1109/CNE.2005.1419607

Ren, Y., & Wu, Y. (2014). Convolutional deep belief networks for feature extraction of EEG signal. Proceedings of the International Joint Conference on Neural Networks, 2850–2853. https://doi.org/10.1109/IJCNN.2014.6889383

Romand, A. (2004). Sharing the power. PEI Power Engineering International, 12(4), 34.

Ruck, D. W., Rogers, S. K., Kabrisky, M., Oxley, M. E., & Suter, B. W. (1990). Letters: The Multilayer Perceptron as an Approximation to a Bayes Optimal Discriminant Function. IEEE Transactions on Neural Networks, 1(4), 296–298. https://doi.org/10.1109/72.80266

Santillan-Guzman, A., Oliveros-Oliveros, J. J., & Morin-Castillo, M. M. (2018). Introducing a Combination of ICA-EMD to Suppress Muscle and Ocular Artifacts in EEG Signals. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2018-July, 1250–1253. https://doi.org/10.1109/EMBC.2018.8512581

Sarma, P., & Barma, S. (2021). Emotion recognition by distinguishing appropriate EEG segments based on random matrix theory. Biomedical Signal Processing and Control, 70(July), 102991. https://doi.org/10.1016/j.bspc.2021.102991

Satuluri, D., Saiteja, B., Milinda, S. K., & Singh, P. (2022). Study of EEG based Emotion Classification using Convolutional Neural Networks. 2022 8th International Conference on Signal Processing and Communication, ICSC 2022, 508–513. https://doi.org/10.1109/ICSC56524.2022.10009458

Sharma, R., & Meena, H. K. (2023). EmHM: A Novel Hybrid Model for the Emotion Recognition based on EEG Signals. 2023 19th IEEE International Colloquium on Signal Processing and Its Applications, CSPA 2023 - Conference Proceedings, March, 75–80. https://doi.org/10.1109/CSPA57446.2023.10087500

Singh, R. K., & Singh, P. A. K. (2014). Frequency Analysis of Healthy & Epileptic Seizure in EEG using Fast Fourier Transform. 2(4), 683–691.

Song, T., Zheng, W., Song, P., & Cui, Z. (2020). EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks. IEEE Transactions on Affective Computing, 11(3), 532–541. https://doi.org/10.1109/TAFFC.2018.2817622

Sourina, O., & Liu, Y. (2011). A fractal-based algorithm of emotion recognition from EEG using arousal-valence model. BIOSIGNALS 2011 - Proceedings of the International Conference on Bio-Inspired Systems and Signal Processing, 209–214. https://doi.org/10.5220/0003151802090214

Srivastava, G., Crottaz-Herbette, S., Lau, K. M., Glover, G. H., & Menon, V. (2005). ICA-based procedures for removing ballistocardiogram artifacts from EEG data acquired in the MRI scanner. NeuroImage, 24(1), 50–60. https://doi.org/10.1016/j.neuroimage.2004.09.041

Subasi, A., & Gursoy, M. I. (2010). EEG signal classification using PCA, ICA, LDA and support vector machines. Expert Systems with Applications, 37(12), 8659–8666. https://doi.org/10.1016/j.eswa.2010.06.065

Subha, D. P., Joseph, P. K., Acharya U, R., & Lim, C. M. (2010). EEG signal analysis: a survey. Journal of Medical Systems, 34(2), 195–212. https://doi.org/10.1007/s10916-008-9231-z

Tao, W., Li, C., Song, R., Cheng, J., Liu, Y., Wan, F., & Chen, X. (2020). EEG-based Emotion Recognition via Channel-wise Attention and Self Attention. IEEE Transactions on Affective Computing, 3045(c), 1–12. https://doi.org/10.1109/TAFFC.2020.3025777

Transactions, W., Processing, S., & Lumpur, K. (2016). Asymmetric ratio and FCM based salient channel selection for human emotion detection using Article in WSEAS Transactions on Signal Processing · January 2008 Asymmetric Ratio and FCM based Salient Channel Selection for. January 2008.

Trier, H. (2012). Fordele ved at strukturere mundtlig kommunikation. Ugeskrift for Laeger, 174(26), 1796.

Vinther, M. (2002). Independent Component Analysis of Evoked Potentials in EEG. 1–23.

Wagh, K. P., & Vasanth, K. (2019). Electroencephalograph (EEG) Based Emotion Recognition System: A Review. In Lecture Notes in Networks and Systems (Vol. 33). Springer Singapore. https://doi.org/10.1007/978-981-10-8204-7_5

Wallstrom, G. L., Kass, R. E., Miller, A., Cohn, J. F., & Fox, N. A. (2004). Automatic correction of ocular artifacts in the EEG: A comparison of regression-based and component-based methods. International Journal of Psychophysiology, 53(2), 105–119. https://doi.org/10.1016/j.ijpsycho.2004.03.007

Wang, X. W., Nie, D., & Lu, B. L. (2011). EEG-based emotion recognition using frequency domain features and support vector machines. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7062 LNCS(PART 1), 734–743. https://doi.org/10.1007/978-3-642-24955-6_87

Xiao, G., Shi, M., Ye, M., Xu, B., Chen, Z., & Ren, Q. (2022). 4D attention-based neural network for EEG emotion recognition. Cognitive Neurodynamics, 16(4), 805–818. https://doi.org/10.1007/s11571-021-09751-5

Xing, X., Li, Z., Xu, T., Shu, L., Hu, B., & Xu, X. (2019). SAE+LSTM: A new framework for emotion recognition from multi-channel EEG. Frontiers in Neurorobotics, 13(June), 1–14. https://doi.org/10.3389/fnbot.2019.00037

Xu, H. (2012). Towards Automated Recognition of Human Emotions using by A thesis submitted in conformity with the requirements Graduate Department of Electrical and Computer Engineering Abstract. 1–155.

Yanagimoto, M., & Sugimoto, C. (2016). Convolutional neural networks using supervised pre-training for EEG-based emotion recognition. Proceedings of the International Workshop on Biosignal Interpretation, November 2016, 72–75.

Yang, H., Han, J., & Min, K. (2019). A multi-column CNN model for emotion recognition from EEG signals. Sensors (Switzerland), 19(21), 1–12. https://doi.org/10.3390/s19214736

Yang, S., & Deravi, F. (2013). Wavelet-based EEG preprocessing for biometric applications. Proceedings - 2013 4th International Conference on Emerging Security Technologies, EST 2013, 43–46. https://doi.org/10.1109/EST.2013.14

Yin, Y., Zheng, X., Hu, B., Zhang, Y., & Cui, X. (2021). EEG emotion recognition using fusion model of graph convolutional neural networks and LSTM. Applied Soft Computing, 100, 106954. https://doi.org/10.1016/j.asoc.2020.106954

Zadeh, L. A. (1994). Fuzzy Logic, Neural Networks, and Soft Computing. Communications of the ACM, 37(3), 77–84. https://doi.org/10.1145/175247.175255

Zali-Vargahan, B., Charmin, A., Kalbkhani, H., & Barghandan, S. (2023). Deep time-frequency features and semi-supervised dimension reduction for subject-independent emotion recognition from multi-channel EEG signals. Biomedical Signal Processing and Control, 85(August 2022), 104806. https://doi.org/10.1016/j.bspc.2023.104806

Zamani, F., & Wulansari, R. (2021). Emotion Classification using 1D-CNN and RNN based On DEAP Dataset. 363–378. https://doi.org/10.5121/csit.2021.112328

Zhang, Jianhai, Chen, M., Zhao, S., Hu, S., Shi, Z., & Cao, Y. (2016). ReliefF-based EEG sensor selection methods for emotion recognition. Sensors (Switzerland), 16(10), 1–15. https://doi.org/10.3390/s16101558

Zhang, Jianhua, Yin, Z., Chen, P., & Nichele, S. (2020). Emotion recognition using multi-modal data and machine learning techniques : A tutorial and review. Information Fusion, 59(March 2019), 103–126. https://doi.org/10.1016/j.inffus.2020.01.011

Zheng, W. L., & Lu, B. L. (2015). Investigating Critical Frequency Bands and Channels for EEG-Based Emotion Recognition with Deep Neural Networks. IEEE Transactions on Autonomous Mental Development, 7(3), 162–175. https://doi.org/10.1109/TAMD.2015.2431497

Zheng, W., Member, S., Lu, B., & Member, S. (2015). Investigating Critical Frequency Bands and Channels for EEG-based Emotion Recognition with Deep Neural Networks. 0604(c), 1–14. https://doi.org/10.1109/TAMD.2015.2431497

Zhou, Wcidong. (2002). ECG Artifacts from EEG Using ICA. Electronics, 206–207.

Zhou, Weidong, & Gotman, J. (2009). Automatic removal of eye movement artifacts from the EEG using ICA and the dipole model. Progress in Natural Science, 19(9), 1165–1170. https://doi.org/10.1016/j.pnsc.2008.11.013

Zima, M., Tichavsk, P., Paul, K., & Krajča, V. (2012). Robust removal of short-duration artifacts in long neonatal EEG recordings using wavelet-enhanced ICA and adaptive combining of tentative reconstructions. Physiological Measurement, 33(8). https://doi.org/10.1088/0967-3334/33/8/N39

Zouridakis, G., Patidar, U., Padhye, N. S., Pollonini, L., Passaro, A., & Papanicolaou, A. C. (2010). Spectral power of brain activity associated with emotion - A pilot MEG study. IFMBE Proceedings, 28, 354–357. https://doi.org/10.1007/978-3-642-12197-5_83

46-Human Emotion94.pdf. (n.d.).

Ackermann, P., Kohlschein, C., Bitsch, J. Á., Wehrle, K., & Jeschke, S. (2016). EEG-based automatic emotion recognition: Feature extraction, selection and classification methods. 2016 IEEE 18th International Conference on E-Health Networking, Applications and Services, Healthcom 2016. https://doi.org/10.1109/HealthCom.2016.7749447

Aftanas, L. I., & Golocheikine, S. A. (2002). Non-linear dynamic complexity of the human EEG during meditation. Neuroscience Letters, 330(2), 143–146. https://doi.org/10.1016/S0304-3940(02)00745-0

Akay, M., & Daubenspeck, J. A. (1999). Investigating the contamination of electroencephalograms by facial muscle electromyographic activity using matching pursuit. Brain and Language, 66(1), 184–200. https://doi.org/10.1006/brln.1998.2030

Akter, S., Prodhan, R. A., Pias, T. S., Eisenberg, D., & Fernandez, J. F. (2022). from Neural Activity.

Al-Nafjan, A., Hosny, M., Al-Wabil, A., & Al-Ohali, Y. (2017). Classification of Human Emotions from Electroencephalogram (EEG) Signal using Deep Neural Network. International Journal of Advanced Computer Science and Applications, 8(9), 419–425. https://doi.org/10.14569/ijacsa.2017.080955

Alarcão, S. M., & Fonseca, M. J. (2019). Emotions recognition using EEG signals: A survey. IEEE Transactions on Affective Computing, 10(3), 374–393. https://doi.org/10.1109/TAFFC.2017.2714671

Algarni, M., Saeed, F., Al-Hadhrami, T., Ghabban, F., & Al-Sarem, M. (2022). Deep Learning-Based Approach for Emotion Recognition Using Electroencephalography (EEG) Signals Using Bi-Directional Long Short-Term Memory (Bi-LSTM). Sensors, 22(8). https://doi.org/10.3390/s22082976

Alhagry, S., Aly, A., & A., R. (2017). Emotion Recognition based on EEG using LSTM Recurrent Neural Network. International Journal of Advanced Computer Science and Applications, 8(10), 8–11. https://doi.org/10.14569/ijacsa.2017.081046

Aljalal, M., Djemal, R., Alsharabi, K., & Ibrahim, S. (2018). Feature Extraction of EEG based Motor Imagery Using CSP based on Logarithmic Band Power, Entropy and Energy. 1st International Conference on Computer Applications and Information Security, ICCAIS 2018, 1–6. https://doi.org/10.1109/CAIS.2018.8441995

Alotaiby, T., El-Samie, F. E. A., Alshebeili, S. A., & Ahmad, I. (2015). A review of channel selection algorithms for EEG signal processing. Eurasip Journal on Advances in Signal Processing, 2015(1). https://doi.org/10.1186/s13634-015-0251-9

Ansari-Asl, K., Chanel, G., & Pun, T. (2007). A channel selection method for EEG classification in emotion assessment based on synchronization likelihood. European Signal Processing Conference, January, 1241–1245.

Arjun, Rajpoot, A. S., & Panicker, M. R. (2022). Subject independent emotion recognition using EEG signals employing attention driven neural networks. Biomedical Signal Processing and

Control, 75(September 2021), 103547. https://doi.org/10.1016/j.bspc.2022.103547

Bartels, G., Shi, L. C., & Lu, B. L. (2010). Automatic artifact removal from EEG - A mixed approach based on double blind source separation and support vector machine. 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10, 5383–5386. https://doi.org/10.1109/IEMBS.2010.5626481

Ben-Zeev, A. (1987). The nature of emotions. Philosophical Studies, 52(3), 393–409. https://doi.org/10.1007/BF00354055

Bista, S., & Adhikari, N. B. (2017). Design of Tri-channel Active Electrode EEG Device for Classification of Motor Imagery Brainwaves. 8914(July 2018), 57–66.

Choi, J. W., & Kim, K. H. (2018). Computational EEG Analysis. 125–145. https://doi.org/10.1007/978-981-13-0908-3

Cimtay, Y., & Ekmekcioglu, E. (2020). Investigating the use of pretrained convolutional neural network on cross-subject and cross-dataset eeg emotion recognition. Sensors (Switzerland), 20(7), 0–20. https://doi.org/10.3390/s20072034

Clynes, M. (1988). Generalised Emotion How it may be produced, and Sentic Cycle Therapy. Emotions and Psychopathology, 107–170. https://doi.org/10.1007/978-1-4757-1987-1_6

Dietrich, A., & Kanso, R. (2010). A review of EEG, ERP, and neuroimaging studies of creativity and insight. Psychological Bulletin, 136(5), 822–848. https://doi.org/10.1037/a0019749

Ekman, P., Friesen, W. V., O'Sullivan, M., Chan, A., Diacoyanni-Tarlatzis, I., Heider, K., Krause, R., LeCompte, W. A., Pitcairn, T., Ricci-Bitti, P. E., Scherer, K., Tomita, M., & Tzavaras, A. (1987). Universals and Cultural Differences in the Judgments of Facial Expressions of Emotion. Journal of Personality and Social Psychology, 53(4), 712–717. https://doi.org/10.1037/0022-3514.53.4.712

Ekman, P., Friesen, W. V, Sullivan, M. O., Diacoyanni-tarlatzis, I., Krause, R., & Scherer, K. (1987). Universals and Cultural Differences in the Judgments of Facial Expressions PERSONALITY PROCESSES AND INDIVIDUAL Universals and Cultural Differences in the Judgments of Facial Expressions of Emotion. November. https://doi.org/10.1037/0022-3514.53.4.712

Ekman, P., & Friesen, W. (1978). Facial action coding system: A technique for the measurement of facial movement. Palo Alto. In Differences among unpleasant feelings. Motivation and Emotion.

Emotions, H. (1978). Human emotion. In Nebraska Symposium on Motivation. Nebraska Symposium on Motivation (Vol. 26). https://doi.org/10.2307/j.ctv1s5nz6h.91

Estepp, J. R., Klosterman, S. L., & Christensen, J. C. (2011). An assessment of non-stationarity in physiological cognitive state assessment using artificial neural networks. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 6552–6555. https://doi.org/10.1109/IEMBS.2011.6091616

Frackowiak, R. S. J. (2017). The functional architecture of the brain. The Brain, 127(2), 105–130. https://doi.org/10.4324/9781351305204-4

Gai, J., & Hu, Y. (2018). Research on Fault Diagnosis Based on Singular Value Decomposition and Fuzzy Neural Network. Shock and Vibration, 2018. https://doi.org/10.1155/2018/8218657

Gao, Z., Wang, X., Yang, Y., Li, Y., Ma, K., & Chen, G. (2020). A Channel-fused Dense Convolutional Network for EEG-based Emotion Recognition. IEEE Transactions on Cognitive and Developmental Systems, 8920(c), 1–1. https://doi.org/10.1109/tcds.2020.2976112

Garg, A., Kapoor, A., Bedi, A. K., & Sunkaria, R. K. (2019). Merged LSTM Model for emotion classification using EEG signals. 2019 International Conference on Data Science and Engineering, ICDSE 2019, 139–143. https://doi.org/10.1109/ICDSE47409.2019.8971484

Garrett, D., Peterson, D. A., Anderson, C. W., & Thaut, M. H. (2003). X k 1 N k = N k Z = f (T X) O = f (T Z). 11(2), 141–144.

Gath, I., & Geva, A. B. (1989). Unsupervised Optimal Fuzzy Clustering. IEEE Transactions on Pattern Analysis and Machine Intelligence, 11(7), 773–780. https://doi.org/10.1109/34.192473

Gliner, J. A., Morgan, G. A., Leech, N. L., Gliner, J. A., & Morgan, G. A. (2021). Measurement Reliability and Validity. Research Methods in Applied Settings, 319–338. https://doi.org/10.4324/9781410605337-29

Gnana, D. A. A. (2016). Literature Review on Feature Selection Methods for High-Dimensional Data Literature Review on Feature Selection Methods for High-Dimensional Data. February. https://doi.org/10.5120/ijca2016908317

Gratton, G., Coles, M. G. H., & Donchin, E. (1983). A new method for off-line removal of ocular artifact. Electroencephalography and Clinical Neurophysiology, 55(4), 468–484.

https://doi.org/10.1016/0013-4694(83)90135-9

Green, C. D. (1912). Livros Grátis. 1.

Healey, J. A., Picard, R. W., Smith, A. C., & Healey, J. A. (2000). Wearable and Automotive Systems for Affect Recognition from Physiology by Certified by .... Wearable and Automotive Systems for Affect Recognition by. 158.

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Iyer, A., Das, S. S., Teotia, R., Maheshwari, S., & Sharma, R. R. (2022). CNN and LSTM based ensemble learning for human emotion recognition using EEG recordings. Multimedia Tools and Applications. https://doi.org/10.1007/s11042-022-12310-7

Iyer, A., Das, S. S., Teotia, R., Maheshwari, S., & Sharma, R. R. (2023). CNN and LSTM based ensemble learning for human emotion recognition using EEG recordings. Multimedia Tools and Applications, 82(4), 4883–4896. https://doi.org/10.1007/s11042-022-12310-7

Izard, C., Fine, S., Schultz, D., Mostow, A., Ackerman, B., & Youngstrom, E. (2001). Emotion knowledge as a predictor of social behavior and academic competence in children at risk. Psychological Science, 12(1), 18–23. https://doi.org/10.1111/1467-9280.00304

James, W. (1884). Mind Association What is an Emotion ? Author (s): William James Published by : Oxford University Press on behalf of the Mind Association Stable URL : http://www.jstor.org/stable/2246769 Accessed : 30-03-2016 19 : 58 UTC Your use of the JSTOR archive ind. 9(34), 188–205.

Jaušovec, N., Jaušovec, K., & Gerlič, I. (2001). Differences in event-related and induced EEG patterns in the theta and alpha frequency bands related to human emotional intelligence. Neuroscience Letters, 311(2), 93–96. https://doi.org/10.1016/S0304-3940(01)02141-3

Jenke, R., Peer, A., & Buss, M. (2014). Feature extraction and selection for emotion recognition from EEG. IEEE Transactions on Affective Computing, 5(3), 327–339. https://doi.org/10.1109/TAFFC.2014.2339834

Ketter, P. (2010). How the brain learns⋯. In T and D (Vol. 64, Issue 5). https://doi.org/10.4135/9781071855324

Kim, M. K., Kim, M., Oh, E., & Kim, S. P. (2013). A review on the computational methods for emotional state estimation from the human EEG. Computational and Mathematical Methods in Medicine, 2013. https://doi.org/10.1155/2013/573734

Kim, Y., & Choi, A. (2020). Eeg-based emotion classification using long short-term memory network with attention mechanism. Sensors (Switzerland), 20(23), 1–22. https://doi.org/10.3390/s20236727

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a rKlimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain Research Reviews, 29(2-3), 169–195. doi:10.1016/S016. Brain Research Reviews, 29(2–3), 169–195. https://doi.org/10.1016/S0165-0173(98)00056-3

Koelstra, S., Member, S., Member, S., Lee, J., Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A., & Patras, I. (n.d.). DEAP : A Database for Emotion Analysis using Physiological Signals. 1–15.

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (1997). International affective picture system (IAPS): Technical manual and affective ratings. NIMH Center for the Study of Emotion and Attention, 39–58.

Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539

Li, Mi, Xu, H., Liu, X., & Lu, S. (2018). Emotion recognition from multichannel EEG signals using K-nearest neighbor classification. Technology and Health Care, 26(S1), S509–S519. https://doi.org/10.3233/THC-174836

Li, Mu, & Member, B. L. S. (2009). 05334139.Pdf. Ieeexplore.Ieee.Org, 1323–1326. https://ieeexplore.ieee.org/abstract/document/5334139/

Liu, H., Zhang, Y., Li, Y., & Kong, X. (2021). Review on Emotion Recognition Based on Electroencephalography. Frontiers in Computational Neuroscience, 15(October), 1–15. https://doi.org/10.3389/fncom.2021.758212

Liu, J., Meng, H., Nandi, A., & Li, M. (2016). Emotion detection from EEG recordings. 2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery, ICNC-FSKD 2016, 1722–1727. https://doi.org/10.1109/FSKD.2016.7603437

Liu, Y., & Fu, G. (2021). Emotion recognition by deeply learned multi-channel textual and EEG features. Future Generation Computer Systems, 119, 1–6. https://doi.org/10.1016/j.future.2021.01.010

Mahajan, R., & Morshed, B. I. (2015). Unsupervised eye blink artifact denoising of EEG data with modified multiscale sample entropy, kurtosis, and wavelet-ICA. IEEE Journal of Biomedical and Health Informatics, 19(1), 158–165. https://doi.org/10.1109/JBHI.2014.2333010

Mehrabian, A. (1996). Pleasure-Arousal-Dominance: A general framework for describing and measuring individual differences in temperament. Current Psychology, 14(4), 261–292. https://doi.org/10.1007/bf02686918

Mohammadi, Z., Frounchi, J., & Amiri, M. (2017). Wavelet-based emotion recognition system using EEG signal. Neural Computing and Applications, 28(8), 1985–1990. https://doi.org/10.1007/s00521-015-2149-8

Moon, Seong-Eun, Jang Soobeom, L. J.-S. (2018). CONVOLUTIONAL NEURAL NETWORK APPROACH FOR EEG-BASED EMOTION RECOGNITION USING BRAIN CONNECTIVITY AND ITS SPATIAL INFORMATION Seong-Eun Moon Soobeom Jang Jong-Seok Lee Republic of Korea. 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2556–2560.

Mukrimaa, S. S., Nurdyansyah, Fahyuni, E. F., YULIA CITRA, A., Schulz, N. D., غسان, د., Taniredja, T., Faridli, E. M., & Harmianto, S. (2016). No 主観的健康感を中心とした在宅高齢者における　健康関連指標に関する共分散構造分析Title. In Jurnal Penelitian Pendidikan Guru Sekolah Dasar (Vol. 6, Issue August).

Murugappan, M. (2013). Human Emotion Recognition Through Short Time Electroencephalogram (EEG) Signals Using Fast Fourier Transform (FFT). 8–10.

Nakisa, B., Rastgoo, M. N., Rakotonirainy, A., Maire, F., & Chandran, V. (2018). Long short term memory hyperparameter optimization for a neural network based emotion recognition framework. IEEE Access, 6, 49325–49338. https://doi.org/10.1109/ACCESS.2018.2868361

Nandini, D., Yadav, J., Rani, A., & Singh, V. (2023). Biomedical Signal Processing and Control Design of subject independent 3D VAD emotion detection system using EEG signals and machine learning algorithms. Biomedical Signal Processing and Control, 85(March), 104894. https://doi.org/10.1016/j.bspc.2023.104894

Ozdemir, M. A., Degirmenci, M., Izci, E., & Akan, A. (2021). EEG-based emotion recognition with deep convolutional neural networks. Biomedizinische Technik, 66(1), 43–57. https://doi.org/10.1515/bmt-2019-0306

Pedrycz, W., & Gomide, F. (2007). Fuzzy Systems Engineering Computing. In Systems Research. http://www.wiley.com/go/p

Pramudita, B. A., Nugroho, Y. D., Ardiyanto, I., Shapiai, M. I., & Setiawan, N. A. (2018).

Removing ocular artefacts in EEG signals by using combination of complete EEMD (CEEMD) - Independent Component Analysis (ICA) based outlier data. Proceeding of 2017 International Conference on Robotics, Automation and Sciences, ICORAS 2017, 2018-March, 1–5. https://doi.org/10.1109/ICORAS.2017.8308056

Press, I. (1927). The James-Lange Theory of Emotions : A Critical Examination and an Alternative Theory Author (s): Walter B . Cannon Published by : University of Illinois Press Stable URL : https://www.jstor.org/stable/1415404 REFERENCES Linked references are available . 39(1), 106–124.

Ramzan, M., & Dawn, S. (2021). Fused CNN-LSTM deep learning emotion recognition model using electroencephalography signals. International Journal of Neuroscience, 0(0), 000. https://doi.org/10.1080/00207454.2021.1941947

Rao, R., & Derakhshani, R. (2005). A comparison of EEG preprocessing methods using time delay neural networks. 2nd International IEEE EMBS Conference on Neural Engineering, 2005, 262–264. https://doi.org/10.1109/CNE.2005.1419607

Ren, Y., & Wu, Y. (2014). Convolutional deep belief networks for feature extraction of EEG signal. Proceedings of the International Joint Conference on Neural Networks, 2850–2853. https://doi.org/10.1109/IJCNN.2014.6889383

Romand, A. (2004). Sharing the power. PEI Power Engineering International, 12(4), 34.

Ruck, D. W., Rogers, S. K., Kabrisky, M., Oxley, M. E., & Suter, B. W. (1990). Letters: The Multilayer Perceptron as an Approximation to a Bayes Optimal Discriminant Function. IEEE Transactions on Neural Networks, 1(4), 296–298. https://doi.org/10.1109/72.80266

Santillan-Guzman, A., Oliveros-Oliveros, J. J., & Morin-Castillo, M. M. (2018). Introducing a Combination of ICA-EMD to Suppress Muscle and Ocular Artifacts in EEG Signals. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2018-July, 1250–1253. https://doi.org/10.1109/EMBC.2018.8512581

Sarma, P., & Barma, S. (2021). Emotion recognition by distinguishing appropriate EEG segments based on random matrix theory. Biomedical Signal Processing and Control, 70(July), 102991. https://doi.org/10.1016/j.bspc.2021.102991

Satuluri, D., Saiteja, B., Milinda, S. K., & Singh, P. (2022). Study of EEG based Emotion Classification using Convolutional Neural Networks. 2022 8th International Conference on

Signal Processing and Communication, ICSC 2022, 508–513. https://doi.org/10.1109/ICSC56524.2022.10009458

Sharma, R., & Meena, H. K. (2023). EmHM: A Novel Hybrid Model for the Emotion Recognition based on EEG Signals. 2023 19th IEEE International Colloquium on Signal Processing and Its Applications, CSPA 2023 - Conference Proceedings, March, 75–80. https://doi.org/10.1109/CSPA57446.2023.10087500

Singh, R. K., & Singh, P. A. K. (2014). Frequency Analysis of Healthy & Epileptic Seizure in EEG using Fast Fourier Transform. 2(4), 683–691.

Song, T., Zheng, W., Song, P., & Cui, Z. (2020). EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks. IEEE Transactions on Affective Computing, 11(3), 532–541. https://doi.org/10.1109/TAFFC.2018.2817622

Sourina, O., & Liu, Y. (2011). A fractal-based algorithm of emotion recognition from EEG using arousal-valence model. BIOSIGNALS 2011 - Proceedings of the International Conference on Bio-Inspired Systems and Signal Processing, 209–214. https://doi.org/10.5220/0003151802090214

Srivastava, G., Crottaz-Herbette, S., Lau, K. M., Glover, G. H., & Menon, V. (2005). ICA-based procedures for removing ballistocardiogram artifacts from EEG data acquired in the MRI scanner. NeuroImage, 24(1), 50–60. https://doi.org/10.1016/j.neuroimage.2004.09.041

Subasi, A., & Gursoy, M. I. (2010). EEG signal classification using PCA, ICA, LDA and support vector machines. Expert Systems with Applications, 37(12), 8659–8666. https://doi.org/10.1016/j.eswa.2010.06.065

Subha, D. P., Joseph, P. K., Acharya U, R., & Lim, C. M. (2010). EEG signal analysis: a survey. Journal of Medical Systems, 34(2), 195–212. https://doi.org/10.1007/s10916-008-9231-z

Tao, W., Li, C., Song, R., Cheng, J., Liu, Y., Wan, F., & Chen, X. (2020). EEG-based Emotion Recognition via Channel-wise Attention and Self Attention. IEEE Transactions on Affective Computing, 3045(c), 1–12. https://doi.org/10.1109/TAFFC.2020.3025777

Transactions, W., Processing, S., & Lumpur, K. (2016). Asymmetric ratio and FCM based salient channel selection for human emotion detection using Article in WSEAS Transactions on Signal Processing · January 2008 Asymmetric Ratio and FCM based Salient Channel Selection for. January 2008.

Trier, H. (2012). Fordele ved at strukturere mundtlig kommunikation. Ugeskrift for Laeger, 174(26), 1796.

Vinther, M. (2002). Independent Component Analysis of Evoked Potentials in EEG. 1–23.

Wagh, K. P., & Vasanth, K. (2019). Electroencephalograph (EEG) Based Emotion Recognition System: A Review. In Lecture Notes in Networks and Systems (Vol. 33). Springer Singapore. https://doi.org/10.1007/978-981-10-8204-7_5

Wallstrom, G. L., Kass, R. E., Miller, A., Cohn, J. F., & Fox, N. A. (2004). Automatic correction of ocular artifacts in the EEG: A comparison of regression-based and component-based methods. International Journal of Psychophysiology, 53(2), 105–119. https://doi.org/10.1016/j.ijpsycho.2004.03.007

Wang, X. W., Nie, D., & Lu, B. L. (2011). EEG-based emotion recognition using frequency domain features and support vector machines. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7062 LNCS(PART 1), 734–743. https://doi.org/10.1007/978-3-642-24955-6_87

Xiao, G., Shi, M., Ye, M., Xu, B., Chen, Z., & Ren, Q. (2022). 4D attention-based neural network for EEG emotion recognition. Cognitive Neurodynamics, 16(4), 805–818. https://doi.org/10.1007/s11571-021-09751-5

Xing, X., Li, Z., Xu, T., Shu, L., Hu, B., & Xu, X. (2019). SAE+LSTM: A new framework for emotion recognition from multi-channel EEG. Frontiers in Neurorobotics, 13(June), 1–14. https://doi.org/10.3389/fnbot.2019.00037

Xu, H. (2012). Towards Automated Recognition of Human Emotions using by A thesis submitted in conformity with the requirements Graduate Department of Electrical and Computer Engineering Abstract. 1–155.

Yanagimoto, M., & Sugimoto, C. (2016). Convolutional neural networks using supervised pre-training for EEG-based emotion recognition. Proceedings of the International Workshop on Biosignal Interpretation, November 2016, 72–75.

Yang, H., Han, J., & Min, K. (2019). A multi-column CNN model for emotion recognition from EEG signals. Sensors (Switzerland), 19(21), 1–12. https://doi.org/10.3390/s19214736

Yang, S., & Deravi, F. (2013). Wavelet-based EEG preprocessing for biometric applications. Proceedings - 2013 4th International Conference on Emerging Security Technologies, EST 2013, 43–46. https://doi.org/10.1109/EST.2013.14

Yin, Y., Zheng, X., Hu, B., Zhang, Y., & Cui, X. (2021). EEG emotion recognition using fusion model of graph convolutional neural networks and LSTM. Applied Soft Computing, 100, 106954. https://doi.org/10.1016/j.asoc.2020.106954

Zadeh, L. A. (1994). Fuzzy Logic, Neural Networks, and Soft Computing. Communications of the ACM, 37(3), 77–84. https://doi.org/10.1145/175247.175255

Zali-Vargahan, B., Charmin, A., Kalbkhani, H., & Barghandan, S. (2023). Deep time-frequency features and semi-supervised dimension reduction for subject-independent emotion recognition from multi-channel EEG signals. Biomedical Signal Processing and Control, 85(August 2022), 104806. https://doi.org/10.1016/j.bspc.2023.104806

Zamani, F., & Wulansari, R. (2021). Emotion Classification using 1D-CNN and RNN based On DEAP Dataset. 363–378. https://doi.org/10.5121/csit.2021.112328

Zhang, Jianhai, Chen, M., Zhao, S., Hu, S., Shi, Z., & Cao, Y. (2016). ReliefF-based EEG sensor selection methods for emotion recognition. Sensors (Switzerland), 16(10), 1–15. https://doi.org/10.3390/s16101558

Zhang, Jianhua, Yin, Z., Chen, P., & Nichele, S. (2020). Emotion recognition using multi-modal data and machine learning techniques : A tutorial and review. Information Fusion, 59(March 2019), 103–126. https://doi.org/10.1016/j.inffus.2020.01.011

Zheng, W. L., & Lu, B. L. (2015). Investigating Critical Frequency Bands and Channels for EEG-Based Emotion Recognition with Deep Neural Networks. IEEE Transactions on Autonomous Mental Development, 7(3), 162–175. https://doi.org/10.1109/TAMD.2015.2431497

Zheng, W., Member, S., Lu, B., & Member, S. (2015). Investigating Critical Frequency Bands and Channels for EEG-based Emotion Recognition with Deep Neural Networks. 0604(c), 1–14. https://doi.org/10.1109/TAMD.2015.2431497

Zhou, Wcidong. (2002). ECG Artifacts from EEG Using ICA. Electronics, 206–207.

Zhou, Weidong, & Gotman, J. (2009). Automatic removal of eye movement artifacts from the EEG using ICA and the dipole model. Progress in Natural Science, 19(9), 1165–1170. https://doi.org/10.1016/j.pnsc.2008.11.013

Zima, M., Tichavsk, P., Paul, K., & Krajča, V. (2012). Robust removal of short-duration artifacts in long neonatal EEG recordings using wavelet-enhanced ICA and adaptive combining of tentative reconstructions. Physiological Measurement, 33(8). https://doi.org/10.1088/0967-3334/33/8/N39

Zouridakis, G., Patidar, U., Padhye, N. S., Pollonini, L., Passaro, A., & Papanicolaou, A. C. (2010).

Spectral power of brain activity associated with emotion - A pilot MEG study. IFMBE Proceedings, 28, 354–357. https://doi.org/10.1007/978-3-642-12197-5_83

APPENDICES A

Turnitin Similarity Report

Nasim Ahmadzadeh-PhD thesis

ORIGINALITY REPORT

15%	11%	12%	1%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.ncbi.nlm.nih.gov Internet Source	3%
2	bura.brunel.ac.uk Internet Source	2%
3	Serkan Kiranyaz, Onur Avci, Osama Abdeljaber, Turker Ince, Moncef Gabbouj, Daniel J. Inman. "1D convolutional neural networks and applications: A survey", Mechanical Systems and Signal Processing, 2021 Publication	1%
4	www.mdpi.com Internet Source	1%
5	"ECAI 2020", IOS Press, 2020 Publication	<1%
6	repository.ntu.edu.sg Internet Source	<1%
7	Nasim Ahmadzadeh Nobari Azar, Nadire Cavus, Parvaneh Esmaili, Boran Sekeroglu, Süleyman Aşır. "Detecting emotions through	<1%

APPENDICES B

Curriculum Vitae

Personal information:

Nasim Ahmadzadeh Nobari Azar

Date of Birth: 06/12/1986

Affiliation: Department of Biomedical Engineering, NEU, Cyprus

E-mail: nasim.ahmadzadeh@neu.edu.tr

Academic Background:

Level	**Institution**	**Program**	**Year**
Ph.D	Near East University	Biomedical Engineering	2024
M.A.	Tabriz.A.I. University	Mechatronic Engineering	2014
B.Sc.	Tabriz University	Computer Science	2010

Teaching Experience

Course	**Institution**	**Level**	**Year**
Data structure (English &Turkish)	Near East University	Undergraduate	23-24
Programing language (C) (English &Turkish)	Near East University	Undergraduate	23-24

Operating system (English &Turkish)	Near East University	Undergraduate	23-24
Programing language (C++) (English &Turkish)	Near East University	Undergraduate	23-24
Animation technologies (PS) (English &Turkish)	Near East University	Undergraduate	23-24
Software Engineering (Turkish)	Near East University	Undergraduate	23-24
System Analysis Methods (Turkish)	Near East University	Undergraduate	23-24

Publications:

1. Deep Learning Methods on Emotion Detection: Input Data Perspective

- Author : Nasim Ahmadzadeh Nobari Azar, Parvaneh Esmaili
- 2021 5th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)

2. Detecting emotions through EEG signals based on modified convolutional fuzzy neural network

- Author : Nasim Ahmadzadeh Nobari Azar, Nadire Cavus, Parvaneh Esmaili, Boran Sekeroglu & Süleyman Aşır
- Scientific reports