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Emotion recognition and artificial intelligence: A systematic review (2014–2023) and research recommendations

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ABSTRACT

Emotion recognition is the ability to precisely infer human emotions from numerous sources and modalities using questionnaires, physical signals, and physiological signals. Recently, emotion recognition has gained attention because of its diverse application areas, like affective computing, healthcare, human–robot interactions, and market research. This paper provides a comprehensive and systematic review of emotion recognition techniques of the current decade. The paper includes emotion recognition using physical and physiological signals. Physical signals involve speech and facial expression, while physiological signals include electroencephalogram, electrocardiogram, galvanic skin response, and eye tracking. The paper provides an introduction to various emotion models, stimuli used for emotion elicitation, and the background of existing automated emotion recognition systems. This paper covers comprehensive searching and scanning of well-known datasets followed by design criteria for review. After a thorough analysis and discussion, we selected 142 journal articles using PRISMA guidelines. The review provides a detailed analysis of existing studies and available datasets of emotion recognition. Our review analysis also presented potential challenges in the existing literature and directions for future research.

1. Introduction

Emotion is a dynamic cognitive and physiological condition that develops in reaction to inputs, like experiences, thoughts, or interactions with people. It includes subjective experience, cognitive processes, behavioral influences, physiological responses, and communication. Therefore, emotion recognition is crucial in the application areas such as marketing, human–robot interaction, healthcare, mental health monitoring, and security [1]. The study of emotions for healthcare includes vast neurological disorders like sleep disorders [2], schizophrenia [3], evaluation of sleep quality [4], and Parkinson's disease [5]. Human emotions can play a key role in detecting physiological conditions like fatigue [6], drowsiness [7], depression [3], and pain [8]. The experts also suggested that variation in emotions are of great importance in the study of autism spectral disorder [9], attention deficit hyperactivity disorder [10], and panic disorder [11]. The study of human emotion is also crucial for human–robot interaction and brain-computer evaluation, where machines are designed to behave like humans for various applications [1]. Therefore, a detailed study of human emotions and automated human emotion recognition is crucial.

1.1. Paradigms of emotion

Distinct brain parts induce different emotions [12]. There are three types of emotional responses: reactional, hormonal, and automatic [13]. According to psychology, emotions are responses to stimuli, associated with qualitative physiological changes [13]. Two basic approaches used to study the nature of emotions are discrete method and the multidimensional approach [13].

1.1.1. Discrete emotions theory

According to this theory, emotions are different and discrete categories, each with its ensemble of cognitive, psychological, and behavioral factors. Emotions can be positive or negative. According to proponents of this hypothesis, there exist a few fundamental emotions that are generally recognized across cultures. There are six basic emotions namely: happiness, sadness, anger, surprise, fear, and disgust [14]. Robert Plutchik provided a comprehensive emotional model called Plutchik's wheel of emotions [15]. Plutchik's wheel consists of eight emotions namely: fear, joy, sadness, trust, anger, surprise, anticipation, and disgust. Other associated emotions, which combines these eight primary emotions are derived by positional intensities. The

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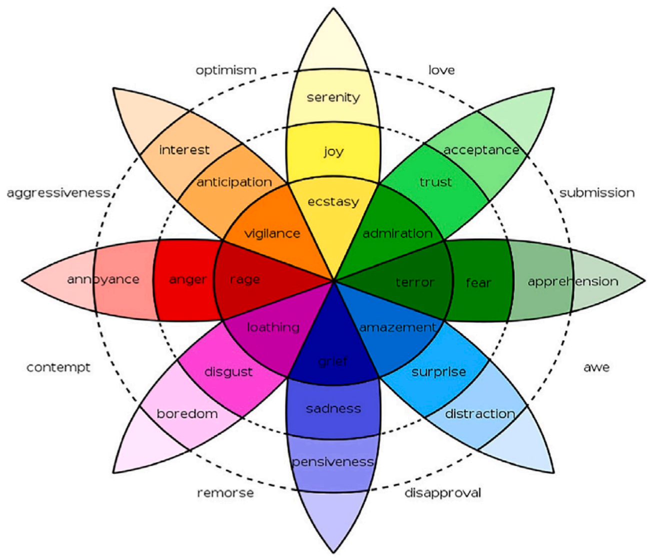

Fig. 1. Plutchik's wheel of emotions [15].

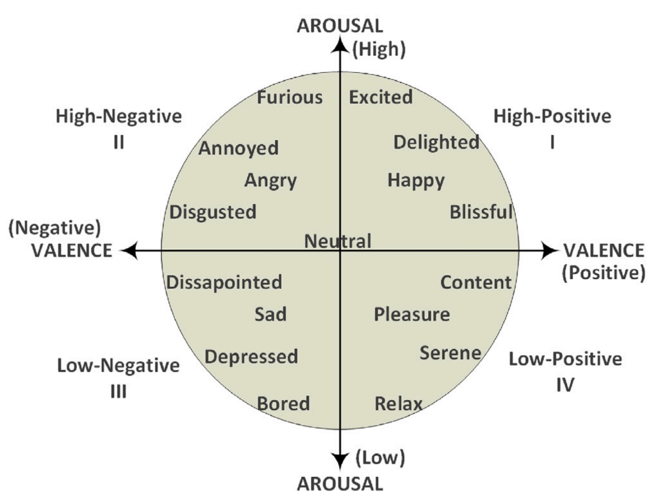

Fig. 2. 2D VA emotion model.

intensity of the emotions increases as we move towards the center of the wheel and vice-versa. Fig. 1 provides an overview of Plutchik's wheel of emotions [15].

1.1.2. Multidimensional emotions theory

The multidimensional approach for emotions acknowledges that emotions are complicated and impacted by numerous elements such as personal experiences, cultural background, and individual variations. It gives a framework for comprehending the richness and complexity of emotional experiences and allows for a more in-depth examination of emotional states. It is categorized as a 2-dimensional (2D) and 3-dimensional (3D) emotional space model. In the 2D emotional space model, emotions are divided into valence (V), which can be positive (Pos) or negative (Neg) and arousal (A), i.e., high activation or low activation. Russell's 2D emotional space model that maps using valence and arousal is shown in Fig. 2 [16].

Similarly, the 3D emotional space model maps various continuous dimensions, such as V (Pos or Neg), arousal (high or low activation), and dominance (D) (feeling in control or feeling controlled). The 3D emotional space model proposed by Mehrabian and Russell is shown in Fig. 3 [17].

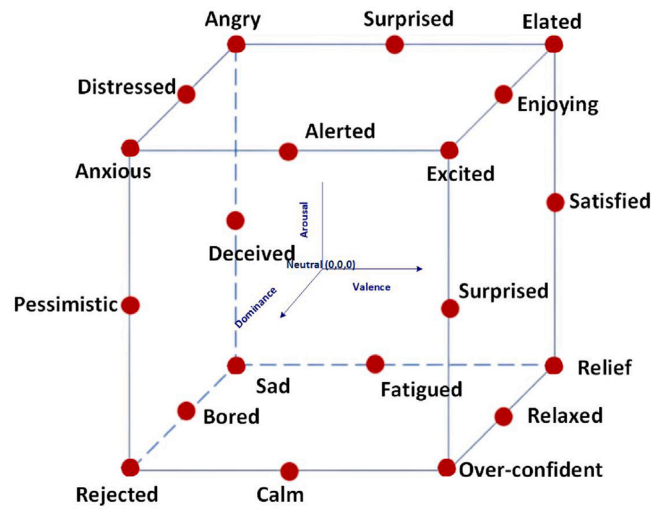

Fig. 3. 3D VAD emotion model.

2. Emotion sensing modalities

Emotion sensing is a technique used to extract human emotions. Over the years, various methods have been adopted to study human emotions. These techniques are broadly classified into three categories, namely: questionnaires, physical, and physiological, as shown in Fig. 4.

2.1. Questionnaires

The questionnaire and self-reports are intended to begin people thinking about the various emotional intelligence competencies as they pertain to them. Various techniques have been developed based on manual assessment of emotions, including positive and negative affect schedule (PANAS) [18], self-assessment manikin (SAM) [19], photographic affect meter (PAM) [20], and experience sampling method (ESM) [21]. PANAS is a psychological technique for assessing and measuring a person's positive and negative emotions. The PANAS questionnaire is divided into two sections: the positive affect scale and the negative affect scale [18]. SAM is a nonverbal pictorial evaluation approach that directly evaluates the valence, arousal, and dominance associated with an individual's emotive reaction to a wide range of stimuli [19]. PAM is a novel affect measurement technique in which users select the photo that best matches their present mood from a large selection [20]. ESM is a research technique used in psychology and related fields to collect real-time data on individuals' experiences, behaviors, and psychological states in their natural environments. It aims to capture momentary or near-real-time assessments of participants' experiences and contexts [21].

2.2. Physical signals

Physical signals for emotion recognition include facial expressions, speech, text, gestures, and body postures [22]. Speech and facial expressions are the most commonly employed mechanisms for emotion identification among physical signals [22]. As a result, we chose to limit our review study to only physical activities based on speech and facial expressions.

2.3. Physiological signals

Physiological signals are the most widely used source for emotion identification. The advantage of physiological signals is that they are activated unintentionally, so cannot be controlled easily by the subject. Other benefits include efficient and low-cost data collection, fewer

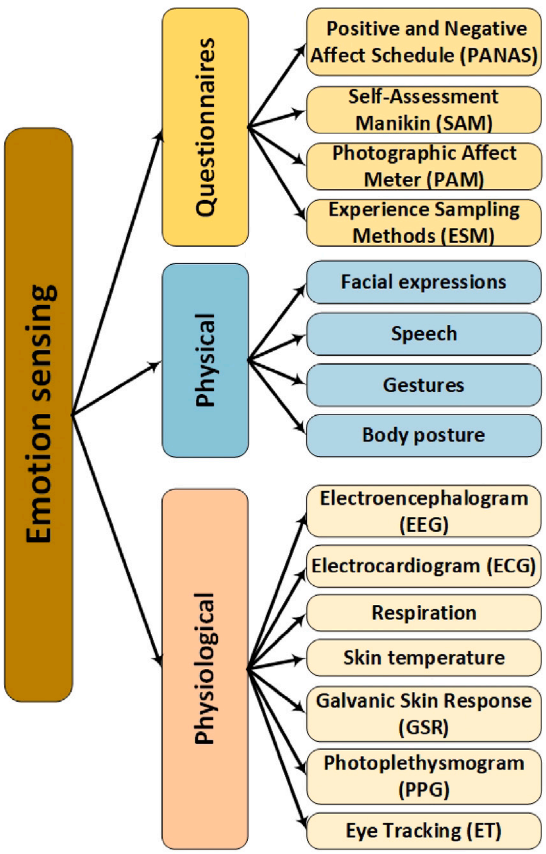

Fig. 4. Branching representation and classification of emotion sensing techniques.

errors caused by light and shadow acquisition, and less invasion of user privacy [22–24]. Electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), respiration (RSP), skin temperature, photoplethysmography, and eye tracking (ET) are the most commonly employed physiological signals for emotion recognition [22]. Among physiological signals, the most often utilized modalities for detecting human emotions are EEG, GSR, ECG, and ET. As a result, these four physiological modalities were included in our review analysis.

3. Overview of automated emotion recognition systems

Automated emotion recognition systems involve several steps for predicting accurate emotional states. The schematic view of the steps in an automated emotion recognition system is shown in Fig. 5. The brief discussion about each step is discussed as follows:

3.1. Source

This first step refers to the part of the body, used for measuring the responses to various inputs. Since our review covers two physical signals (speech and facial expressions) and four physiological signals (EEG, ECG, GSR, and ET), therefore, acquisition sources are limited to eyes, speech, brain, heart, skin, and face.

3.2. Stimuli

Stimuli are any items, events, or conditions that cause an organism, such as a person or an animal, to respond or react. Stimuli are commonly employed in psychology and research to elicit responses or behaviors for studying and understanding various psychological processes. Stimuli can include situations, scenarios, or social interactions that elicit emotional, cognitive, or behavioral responses. Well-known stimuli for eliciting the targeted emotions are virtual reality (VR), images, video games, music, audio/video clips, audio, and/or videos [25–27]. Based on the type of stimulus various emotions are elicited and are ranked manually using a questionnaire using SAM, PANAS, PAM, ESM, or other similar techniques.

3.3. Input signals

Input signals are pre-processed for effective analysis. Pre-processing refers to the steps or procedures performed on raw data prior to analysis or further processing. Pre-processing is critical in data analysis because it improves data quality, reduces noise or extraneous information, and prepares the data for effective analysis and modeling. The specific pre-processing steps are decided by the nature of the data and the goals of the study. Typically, the steps involved in pre-processing are data cleaning (removal of artifacts and other noise sources), data integration, data transformation, data sampling, and data scaling.

3.4. Feature extraction

In data analysis and machine learning (ML), feature extraction refers to translating raw data into a set of relevant and representative characteristics that may be used for further modeling. It seeks to extract from data important information or patterns that encapsulate the key traits or properties of the underlying phenomenon. The goal of feature extraction is to find and choose a subset of attributes that best capture the subtle details in the data while rejecting redundant or unnecessary data. This procedure reduces the data's dimensionality, making it more understandable and suited for analysis or modeling activities. The most common features include statistical features, nonlinear features, frequency-domain features, entropy features, time–frequency-based features, image-vision-based features, fractal dimensions, nonlinear decomposition, domain-specific features, and deep learning (DL) features.

3.5. Feature selection

The process of choosing a subset of pertinent characteristics from a set of features that are present in a dataset is known as feature selection. It attempts to choose the most discriminative and informative features that contribute the most to the analysis or prediction while avoiding duplicate or unnecessary features. The choice of features is crucial since it may speed up computation, reduce overfitting, boost interpretability, and enhance model performance. The most common feature selection techniques include dimensionality reduction (principle component analysis or independent component analysis), statistical or univariate analysis (chi-squared test, ANOVA, or correlation), regularization techniques (Lasso (L1 regularization) and Ridge (L2 regularization)), feature selection algorithms or wrapper methods (recursive feature elimination, sequential feature selection, and tree-based methods, or ensemble based methods).

3.6. Classification

It is a crucial step in an automated detection system that is used to categorize the values of the variables to its subsequent classes. It involves decision-making using ML or DL techniques. ML techniques involve, among others, support vector machine (SVM), k-nearest neighbor (KNN), decision tree (DT), artificial neural network (ANN), random forest (RF), logistic regression, linear discriminant analysis are some of the most widely used techniques. Convolutional neural network (CNN), long-short term memory (LSTM) networks, deep neural networks (DNN), multilayer perceptron (MLP), recurrent neural network

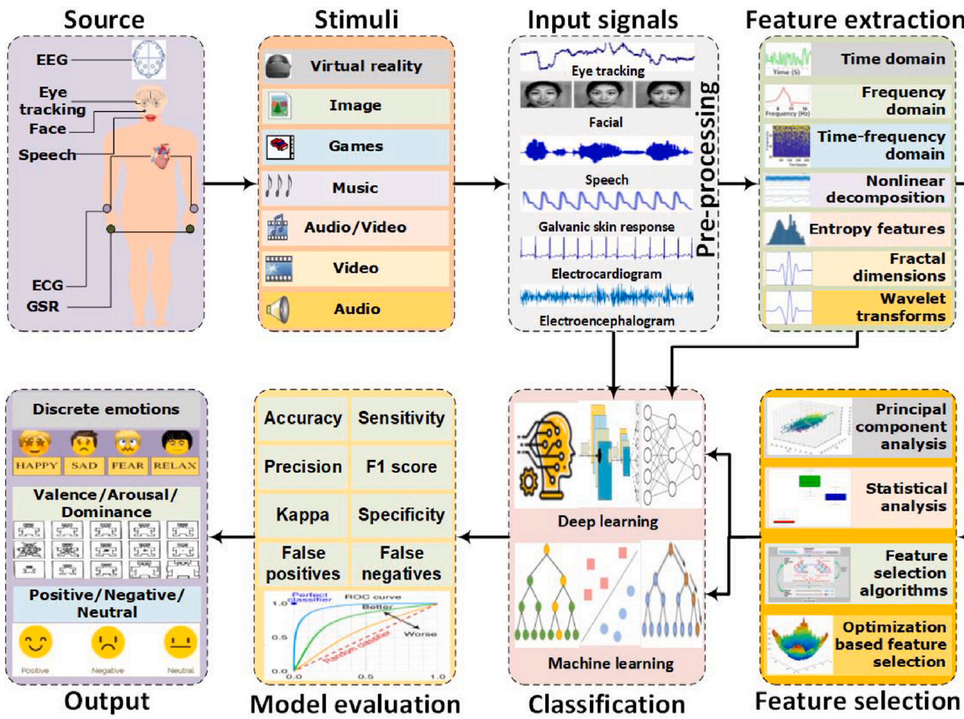

Fig. 5. Schematic diagram of steps involved in an automated emotion recognition system.

(RNN), generative adversarial networks (GAN), gated recurrent units, self-organizing maps, deep reinforcement learning, deep transfer learning, autoencoders (AE), transformers, and deep belief network (DBN) are some of the state-of-the-art DL models.

3.7. Model evaluation

An ML or classification model's quality and efficacy are assessed using performance measures. These metrics give numerical evaluations of the model's performance regarding predictions and generalizability to new data. Particular challenge, kind of data, and the required assessment standards influence the choice of performance indicators. Some famous indicators of success for ML/DL models are accuracy (ACC), recall, specificity, precision, confusion matrix, area under the receiver operating characteristic curve (AUC-ROC), and F-1 score.

4. Motivation and highlights of the review study

In the last decade, several review papers have been published for emotion recognition and decision-making. We have performed a comprehensive search by scanning the relevant review articles published recently, and identified significant limitations, before designing our systematic review as shown in Fig. 6.

4.1. Existing emotion recognition review studies

Hasnul et al. [28] presented a review of ECG-based emotion recognition and their applications. Their review strategy did not employ PRISMA guidelines and was limited to ECG signals. The authors further discuss the application areas confined to healthcare with limited discussion on challenges and future directions. Bota et al. [29] carried out a comprehensive review on emotion recognition using physiological signals and ML techniques. Their review study failed to employ a systematic review strategy using PRISMA guidelines. Their review study did not discuss application areas, presented limited discussion, and limited future directions. Singh and Goel [30] presented a systematic review of emotion recognition using speech signals following PRISMA guidelines. Their method covered the application of ML and DL techniques, but failed to cover research challenges and comprehensive research directions. Kamble and Sengupta [31] presented a review on emotion recognition using EEG signals without following PRISMA guidelines. They presented a detailed analysis of feature extraction methods and decision-making using ML and DL techniques. Their review method did not explore research challenges and future directions. Zhang et al. [32] presented a review of EEG signals and ML techniques for emotion recognition without PRISMA guidelines. The authors presented a comprehensive study on existing methods, open challenges, and future directions. Adyapady and Annappa [33] provided a comprehensive review of facial image-based emotion recognition using ML and DL techniques. Their emotion detection review method does not involve PRISMA guidelines. The authors discussed various techniques, datasets, and a few applications of emotion recognition. Ba and Hu [34] performed a systematic review following PRISMA guidelines on emotion recognition using wearables in education. Their review study showed that portable and accurate wearable devices adopting electro-dermal activity and heart rate signals are common for emotion detection in education.

4.2. Motivation for the current review study

Human emotions are important markers for different states of conditions and behavioral analysis. Recently, several review studies have been conducted, focusing on numerous applications and detection techniques. After doing a comprehensive literature analysis on human emotion recognition review articles, the following gaps have been identified.

- Many emotion recognition studies have been performed without PRISMA guidelines [28,29,31–33].
- The majority of the review articles previously published for emotion recognition focused on a single modality i.e., either physiological signal, speech, or facial images [28,31–33].
- The emotion recognition studies on physiological signals are confined to EEG signals or ML techniques [31,32].

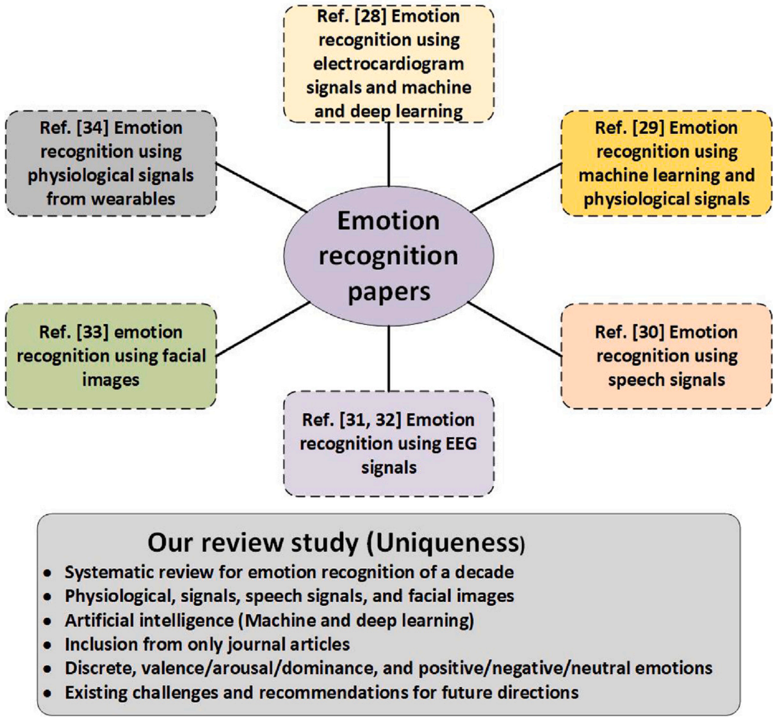

Fig. 6. Comparison and uniqueness of our review study with existing review papers published for emotion recognition.

- A little discussion on research challenges and applications [28–33].
- Limited directions for future research [28–33].

The above-listed gaps motivate us to write a comprehensive and systematic review of emotion recognition using different modalities. We have also focused on a detailed discussion of datasets, feature extraction techniques, and inclusion of artificial intelligence (AI). Our review study presents a detailed analysis and comprehensive summary of existing feature extraction and classification techniques. In addition, our review study includes a detailed analysis of current research gaps, potential application areas, and directions for future research in emotion recognition.

4.3. Salient features of our systematic review

The uniqueness and salient features of our review study are listed as follows and shown in Fig. 7:

1. **Comprehensive use of datasets:** Our review study explores a comprehensive search strategy of different databases. The authors have scanned renowned databases, including Web of Science, MEDLINE, PubMed/PubMed Central, IEEE Explore, Scopus, Wiley, and others for selecting the most relevant research studies.
2. **Systematic review:** Our developed review study follows strict PRISMA guidelines for selecting relevant research articles.
3. **Time window:** We have considered a time window of last 10 years, for scanning and selecting the articles included in the review.
4. **Multi-modal emotion recognition:** We have included physiological signals (EEG, ECG, ET, and GSR) and physical activity (speech and facial expression). In addition, we have used AI comprised of ML and DL techniques used for emotion recognition.
5. **Diverse emotion model:** We have included articles on discrete and multi-dimensional emotional models to develop our review study. Also, we have confined our search for articles to peer-reviewed journals.

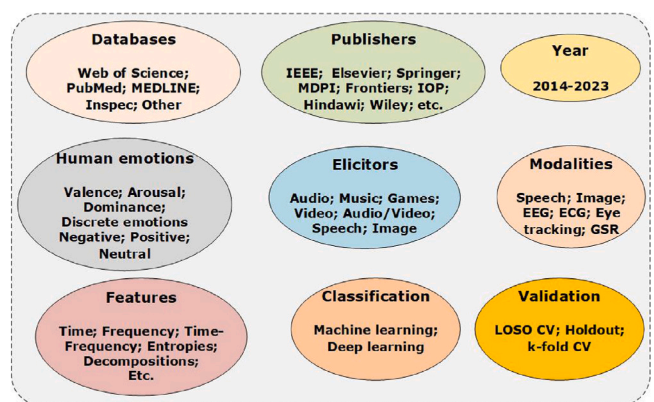

Fig. 7. Highlights and key points included in the review method for emotion recognition.

6. **Datasets:** We have also presented a comprehensive analysis of the available datasets used for emotion recognition using different modalities.
7. **Analysis:** We have presented a detailed analysis and discussion of existing studies included in the current review.
8. **Challenges and future Directions:** We identified current challenges, presented a detailed discussion and future directions for research. We also explored the application areas of emotion recognition in various fields.

5. Review method

The current systematic review uses the recommended reporting elements for systematic reviews and meta-analyses (PRISMA) guidelines [35]. The review protocol includes search strategies, selection criteria, selection standards, and data extraction. The details of search, selection, and extraction strategies are covered in the following subsections:

Table 1
Criteria adopted for inclusion and exclusion for article selection.

Inclusion	(i) emotion recognition (ii) classification of emotions using EEG signals (iii) emotion recognition and EEG signals (iv) detection of emotion using EEG signals (v) emotion recognition using physiological signals (vi) detection of emotions using ECG signals (vii) emotion recognition using ECG signals (viii) automated emotion recognition using physiological signals (ix) machine learning and deep learning for emotion recognition (x) GSR and emotion classification (xi) galvanic skin response for emotion detection (xii) automated emotion classification using GSR (xiii) eye tracking and emotion classification (xiv) emotion detection using eye tracking (xv) automated emotion detection and eye tracking (xvi) speech and emotion classification (xvi) speech-based emotion recognition (xvii) automated emotion detection using speech (xviii) facial images and emotion classification (xix) automated system for emotion classification using facial images (xx) emotion and facial images (xxi) automated human emotion recognition (xxii) deep learning based emotion detection using facial images
Exclusion	(i) extension or repeated articles (iii) articles published before 2014 (iii) conference articles (iv) non-English research articles (v) book chapters (vi) non-peer reviewed articles (vii) articles with statistical analysis

5.1. Search strategy and selection criteria

The search for relevant emotion recognition studies starts with modalities like physiological signals, including EEG, ECG, GSR, and ET, speech signals, and facial images. We have also looked for AI, including ML and DL. We searched famous electronic databases, which include Web of Science, MEDLINE, PubMed/PubMed Central, IEEE Explore, Scopus, and Wiley to locate the desired articles on emotion recognition. The authors limited their articles search to English language and journal articles. The search window for articles is adjusted to the last 10 years, covering articles published between December 2013 to July 2023. The focus of the search was limited to physiological signals, emotion recognition or classification, facial images, and AI. The key terms used to scan the relevant physiological signals covers "electroencephalogram", "electrocardiogram", "galvanic skin response", "eye tracking", "electrooculogram", "EEG", "GSR", "EOG", "ET", "ECG", "EKG", and "speech". The search criteria for emotions includes "emotion classification", "emotion detection", "emotion recognition", "emotion identification", and "emotion charting". The search for image-based emotion recognition include "facial images", "images", "facial data", and "faces". Finally, "deep learning", "machine learning", "automated recognition", "classification", and "artificial intelligence" have been used for searching artificial intelligence.

The search criteria for scanning and selecting appropriate research articles for emotion recognition was tedious and time-consuming. Therefore, we have adopted inclusion and exclusion criteria for selecting relevant articles for our review study. Table 1 shows the adopted criteria for including and excluding the research articles. Initially, in stage one, authors reviewed the title, keywords, and abstract of articles. After discussion, the authors decided to finalize the inclusion/exclusion criteria for the articles. After initial screening, the full text of the remaining articles was examined and analyzed in stage two.

5.2. Results

Fig. 8 shows the PRISMA guidelines used for screening and selecting relevant emotion recognition articles. We have categorized article shortlisting into three steps: identification, screening, and inclusion. Initially, a total of 14 257 articles were identified from six prestigious databases and registers, including Web of Science, PubMed, MEDLINE, Inspec, Scopus, and others. Based on the relevance of the study, we selected 3846 articles, and discarded the remaining before screening. During the screening stage, we retrieved 968 articles, of which 234 were screened for further assessment and excluded others. During the final inclusion stage, out of 234 articles, 92 were excluded based on the exclusion criteria, and 142 were selected for review. The distribution includes 44 articles based on EEG, 20 articles on ECG-based emotion recognition, 16 articles for GSR-based emotion recognition, 6 articles on ET, and 28 articles each for speech- and facial image-based emotion recognition. However, some articles are common for EEG-, ECG-, and GSR-based emotion recognition. Fig. 9 shows the distribution of articles based on time and publishers. The time-based analysis reveals that the highest number of articles belongs to the year 2022, whereas, Elsevier is the mostly preferred publisher followed by IEEE.

6. Summary of emotion recognition studies using EEG signals

The authors have selected 44 articles based on EEG-based emotion recognition. In addition, 5 articles used EEG signals along with ECG and GSR modalities taking a total count to 49. Table A.3 presents a detailed summary of the EEG-based emotion recognition automated system.

6.1. Highlights of EEG-based emotion recognition

The time-based analysis reveals that the highest number of 12 studies have been reported from the year 2020, followed by 2021 and 2019 with 9 studies each. Elicitation of emotions from audio and video stimuli has been most widely preferred during EEG acquisition. EEG-based emotion recognition has been conducted mostly on public EEG datasets over private datasets. DEAP, SEED/SSED IV, and DREAMER have been used most with individual occurrences of 22, 16, and 9 times, respectively. Classification of emotions based on V/A/D is preferred over discrete emotions and positive (Pos)/Negative (Neg)/Neutral (Neu). Classification of four basic emotions in the discrete model is highly preferred over other discrete classification models. Extraction of nonlinear and statistical features is preferred for direct feature extraction. For frequency domain features, power spectral density (PSD) is the most commonly used technique for EEG-based emotion recognition. Decomposition techniques like wavelet-based decomposition, empirical mode decomposition (EMD), and variational mode decomposition (VMD) have been used the most to extract relevant features. In addition, short-time Fourier transforms (STFT), Cohen's class, and S-transform have been utilized to extract time-frequency representation (TFR). The validation using k-fold cross-validation (FCV), particularly 10 FCV has been preferred over leave one subject out/ leave one out validation (LOSO) and holdout validation. ML models are used higher than DL models for the classification of emotion. The detailed distribution summary of the decision-making model is shown in Fig. 10. It is evident from Fig. 10 that SVM and its variant have been used the most, followed by KNN and extreme learning machine (ELM) classifier. In DL taxonomy, CNN has been used ten times followed by LSTM-based decision-making models.

6.2. Details of the EEG-based emotion datasets

Table B.9 presents the details of the EEG datasets used by the EEG-based emotion recognition studies. A total of 21 diverse EEG-based emotion datasets have been used by included studies. It includes 15 publicly available datasets and 6 private datasets. One study each used music, games, and VR as an elicitor, 2 studies used images, and remaining used AV stimulus.

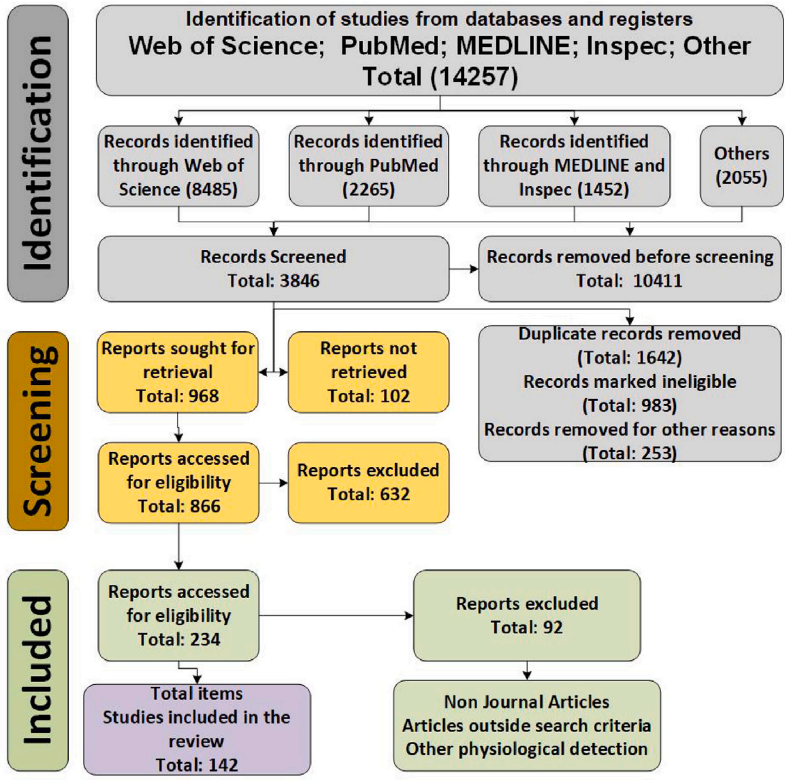

Fig. 8. Overview of the PRISMA guidelines followed during the selection of the articles in the systematic review.

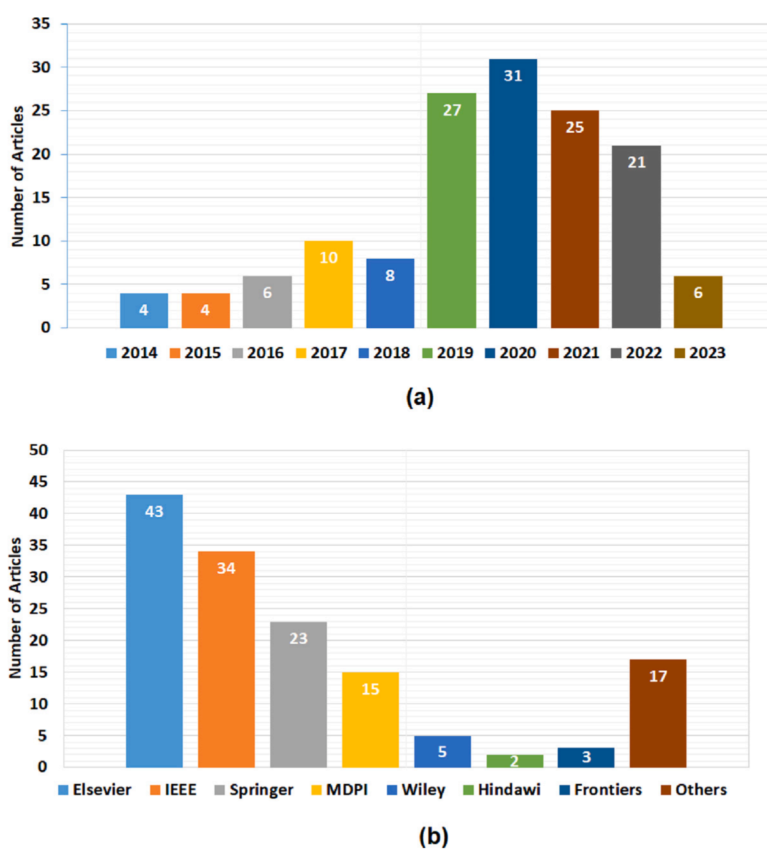

Fig. 9. Details of the papers included after PRISMA guidelines (a) Publisher-based distribution and (b) Time-based analysis (Year-wise distribution).

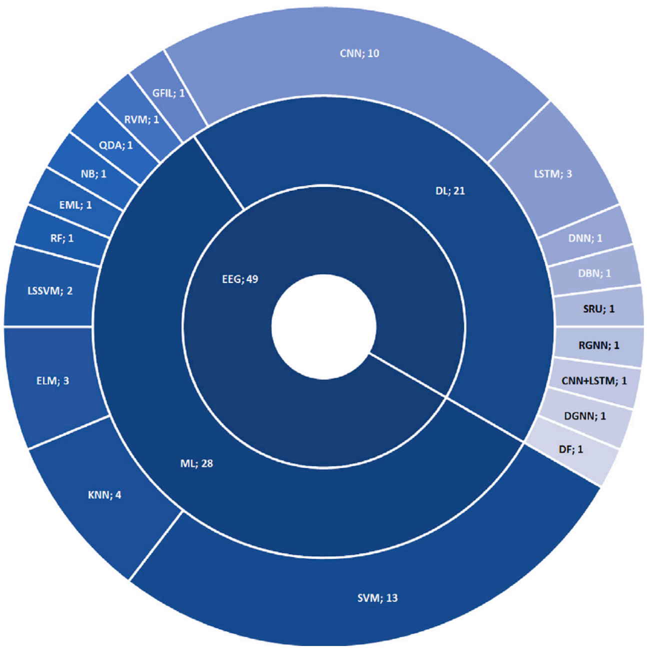

Fig. 10. Summary of distribution for emotion recognition studies using EEG signals.

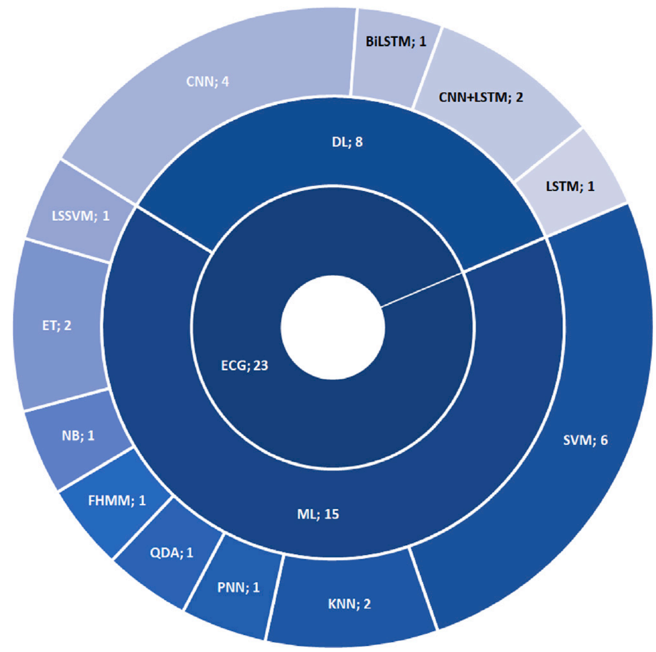

Fig. 11. Summary of distribution for emotion recognition studies using ECG signals.

7. Summary of emotion recognition studies using ECG signals

A total of 23 articles have been discussed for ECG-based emotion recognition as shown in Table A.4. Out of 23 articles, 20 articles are related to only ECG-based emotion recognition and articles are combined with EEG- and GSR-based studies.

7.1. Highlights of ECG-based emotion recognition

The year-wise distribution of ECG-based emotion recognition reveals that four articles belongs to the years 2017, 2020, and 2021, respectively. The year 2022 has three articles, two articles each for 2019 and 2023, and one for 2014, 2015, and 2018, respectively. Audio/video and video-only based emotion elicitation have been the most common choice, followed by images and music-based emotions contributing equally to emotion elicitation. The researchers preferred public ECG datasets over private ones for emotional state detection. From the public datasets, five times DREAMER dataset has been used, three each in the case of AMIGOS and ASCERTAIN, WESAD and MAHNOB-HCI each used twice, and others once. Classification of V/A/D has been the highest, followed by discrete emotion (four class) classification. Extraction of features directly from ECG signals is preferred the most. These include nonlinear features (NLF), statistical features (STSF), time-domain features (TDF), heart rate variability (HRV), frequency-domain features (FDF), and rhythmic features. In addition, wavelet-based decomposition and EMD methods have been used for extracting representative features. The validation of the classification model mostly used ten-FCV, followed by holdout and LOSO CV. The distribution of decision-making models for ECG emotion classification is shown in Fig. 11. As evident from Fig. 11, 15 times ML models have been used for emotion recognition and 8 times the usage of DL models. SVM and KNN are most efficient in ECG classification in ML taxonomy, while CNN is more common in DL taxonomy.

7.2. Details of the ECG-based emotion datasets

A total of 18 ECG-based emotion datasets have been used in all the articles included in our review. The details of the ECG-based emotion datasets are shown in Table B.10. Emotion recognition studies explored privately developed datasets over public ECG datasets. Audio/video stimuli have been the most preferred choice to elicit emotions, followed by music and image-based stimuli. The acquisition system used three electrode settings. V/A/D emotion classification type has been adopted the most, followed by discrete emotion classification.

8. Summary of emotion recognition studies using GSR signals

A total of 18 articles have been discussed for GSR-based emotion recognition as shown in Table A.5. Out of 18 articles, 16 articles used only GSR-based emotion recognition, and 2 articles combined with EEG- and ECG-based studies.

8.1. Highlights of GSR-based emotion recognition

Time-based analysis of GSR-based emotion recognition included in the review shows that the highest number of articles (4 articles) were from 2020. The year 2016 and 2017 includes three research articles each, while the years 2018, 2019, 2021, and 2022 reported two articles each, respectively. There are no articles from 2014, 2015, and 2023. Elicitation of emotions using audio/video and music-based stimuli was adopted most frequently. The DEAP and ASCERTAIN datasets were used three times each, while the other one time. Researchers adopted private GSR datasets for emotion recognition (11 times) over public datasets (9 times). The classification of emotions in terms of V/A and discrete emotions contributed equally. Direct extraction of STSF, NLF, rhythmic features, and entropy features from GSR signals have been used for the classification. Also, decomposition techniques like wavelet decomposition, DWT, and EMD to extract information from GSR have been used. The validation strategy also includes holdout and k-fold CV. The classification strategies adopted for emotion recognition are shown in Fig. 12. It has been observed from Fig. 12 that ML models have been used more often than that DL models. Within ML models, SVM and their variants have been the most common classification strategy (7 times), followed by KNN and ensemble techniques (ET) used two times each. CNN models, a combination of CNN with long-short-term memory (LSTM) have been the favorites in DL models. Audio/video stimuli have been the most preferred choice to elicit emotions, followed by music stimuli (see Fig. 12).

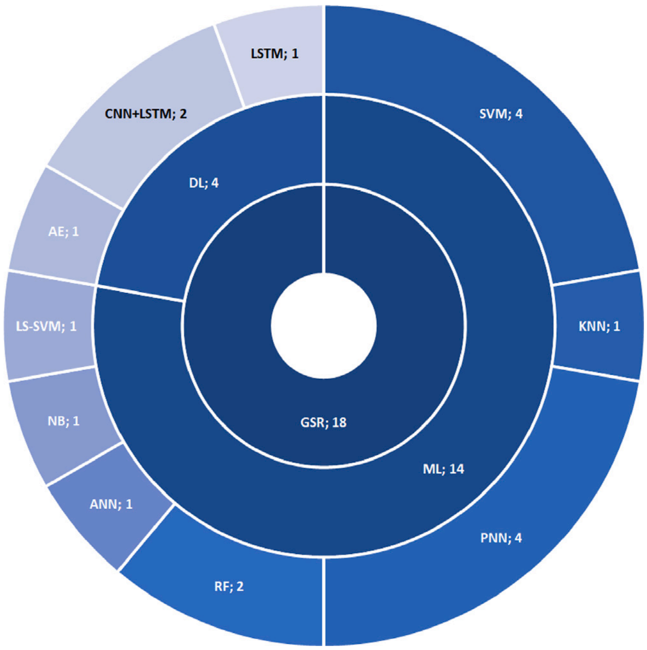

Fig. 12. Summary of distribution for emotion recognition studies using GSR signals.

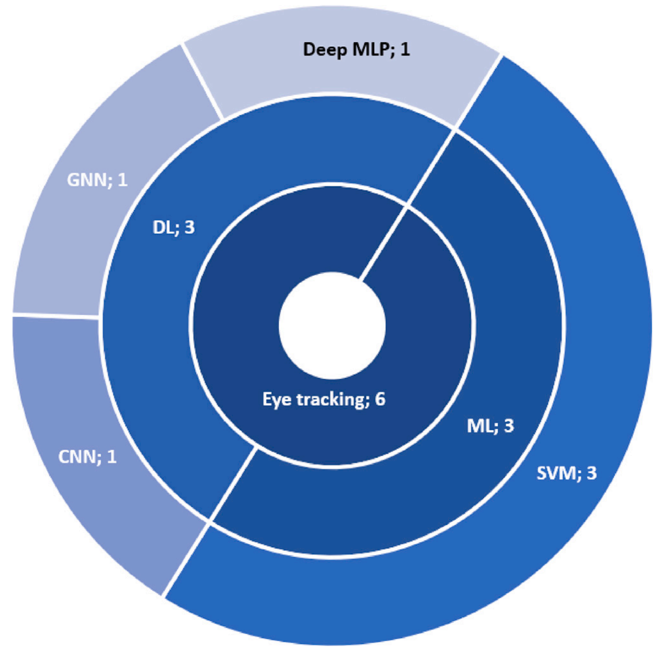

Fig. 13. Summary of distribution for emotion recognition studies using ET signals.

8.2. Details of the GSR-based emotion datasets

A total of 14 GSR-based emotion datasets have been used in all the articles included in our review. The details of the GSR-based emotion datasets are shown in Table B.11. Emotion recognition studies explored privately developed datasets over public datasets. Audio/video stimuli have been the most preferred choice to elicit emotions, followed by music and image-based stimuli. The acquisition system used three electrode settings. Classification of emotions from discrete emotion models was explored the most, followed by V/A/D and affect states.

9. Summary of emotion recognition studies using ET signals

The detailed summary of ET-based emotion recognition is shown in Table A.6. A total of 6 articles have been selected and included in our review analysis.

9.1. Highlights of ET-based emotion recognition

Year-wise distribution of the articles shows that the highest number of three articles was published in 2021. In addition, the years 2019, 2020, and 2023 reported one article each. Three articles have used video-based emotion elicitation, two articles reported image-based emotion elicitation, and one article used virtual reality. Five articles used the private ET emotion dataset, while only one ET dataset is publicly available. All the articles have explored discrete emotion classification, four of them using four basic emotion categories. STSF, FDF, and NLP features have been extracted directly from ET signals. One article used signal transformation using FFT and STFT. Holdout validation and LOSO CV was the most prevalent for model validation. The breakout of decision-making models for classification is shown in Fig. 13. It is seen from Fig. 13 that for ET-based emotion classification, DL models have been preferred over ML techniques.

9.2. Details of the ET-based emotion datasets

The details of the ET-based emotion dataset are shown in Table B.12. The summary shows that emotion recognition has used independent datasets for their analysis. Also, out of the six datasets used for emotion recognition, five are privately developed, while one is public. This limits the applicability and usability of ET-based emotion recognition. Elicitation of emotions from videos was used three times, images were used twice, and virtual reality was explored once.

10. Summary of emotion recognition studies using speech signals

For speech-based emotion recognition, we have selected 28 journal articles. The summary of these articles used in the review analysis is shown in Table A.7.

10.1. Highlights of speech-based emotion recognition

As evident from the summary of Table A.7, one article each has been included from the years 2014, 2015, and 2017, respectively. The highest articles, i.e. 8, have been reported from the year 2019, followed by 6 articles in 2020, 5 in 2021, and 3 each in the years 2018 and 2022, respectively. The audio/video or audio based have been used the most for emotion elicitation. The dataset analysis reveals that EMO-DB, RAVDEES, CASIA, and IEMOCAP datasets have been the most preferred choices for model testing. The highest strength of speech-based emotion recognition is that multiple datasets have been used for method verification. Public speech emotion datasets have been selected over private datasets. Discrete type classification of emotions has been adopted for all the studies. Power spectral density (PSD), Mel-frequency cepstrum coefficients (MFCC), Mel spectrogram (MSG), STFT, and variants of wavelet transform (WT) have been adopted the most for feature extraction. Model validation using holdout CV was preferred the most for speech, followed by k-FCV, and the least with LOSO CV, respectively. The summary and distribution of the classification techniques used for emotion recognition are shown in Fig. 14. The distribution shown in Fig. 14 reveals that DL models have an edge over ML models for speech-based emotion recognition. The usage of the SVM classifier was reported 7 times and the extreme learning machine (ELM) classifier 2 times in ML-based decision-making. For DL models, CNN was used 10 times, followed by LSTM and BiLSTM 3 times.

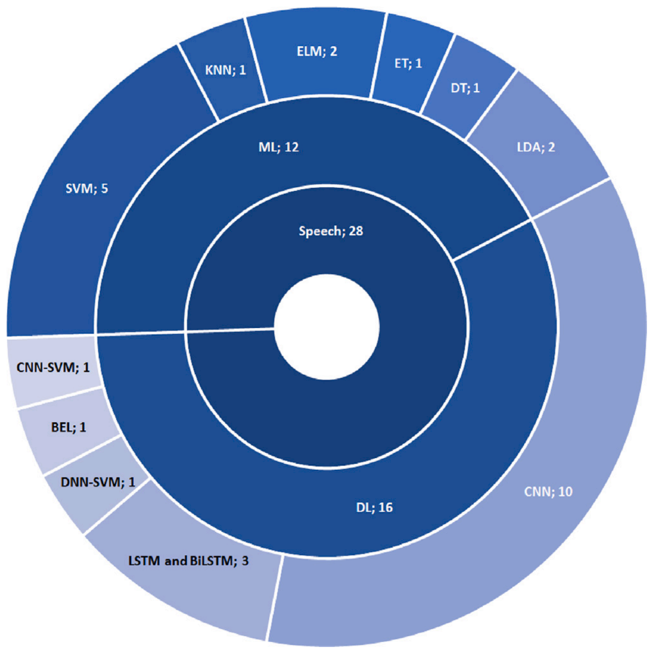

Fig. 14. Summary of distribution for emotion recognition studies using speech signals.

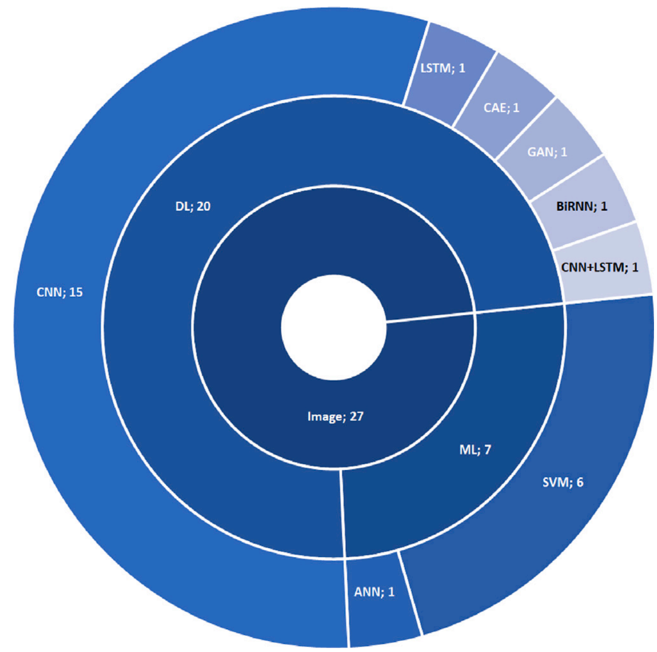

Fig. 15. Summary of distribution for emotion recognition studies using facial images.

10.2. Details of the speech-based emotion datasets

The detailed summary of the speech-based emotion dataset is shown in Table B.13. The details revealed that 19 datasets have been utilized in speech-based emotion recognition studies. Among these, 11 datasets are publicly available, while 8 datasets are private. Emotion classification using speech-preferred discrete emotion models with several emotions varying from 3 to 12.

11. Summary of emotion recognition studies using facial images

The review included 28 articles on the recognition of emotions using facial images. Table A.8 presents a summary of facial image-based emotion recognition.

11.1. Highlights of facial images-based emotion recognition

The summary provided in Table A.8 reveals that the highest number of articles have been from the years 2019 and 2020, respectively. Facial image-based emotion recognition has one article each from the years 2015, 2016, and 2017, respectively. A total of 2, 4, and 5 articles have been extracted from the years 2023, 2021, and 2022. The datasets CK+ and JAFFE have been the most commonly used facial image datasets. In addition, FER2013, RAF-DB, and AffectNet have also been used in many studies. The facial image-based emotion recognition studies have validated their model on multiple datasets. The majority of the facial image datasets are publicly available. A discrete emotion model is used for classification with several emotions varying from 2 to 10. Features based on geometric or texture of facial patterns are preferred. The validation of the model using holdout CV followed by k-FCV strategies is most common. The distribution of decision-making models for facial images is shown in Fig. 15. Out of 28 articles, as many as 20 articles have preferred DL models for classification, 7 used ML models, while the status of one article is unknown. For ML models, the SVM classifier has been the most preferred, while CNN has an upper edge over other DL models.

11.2. Details of the facial image-based emotion datasets

The details of facial image datasets used for emotion recognition is shown in Table B.14. A total of 24 datasets have been used in the studies included in our review, 21 datasets are publicly available, while only 3 datasets are private. All the datasets used discrete emotion classification.

12. Discussion

Emotion recognition using physiological signals like EEG, ECG, and GSR has been majorly classified as valence, arousal, and dominance as evident from Tables A.3, A.4, and A.5. In the case of the ET signals, speech, and images, discrete emotion classification has been preferred as shown in Tables A.6, A.7, and A.8. Audio/video-based elicitation has been the most common and preferred technique. The following subsection presents the discussion on individual modalities for emotion recognition.

12.1. Takeaways from EEG-based emotion recognition studies

EEG signals are nonlinear and non-stationary with multi-frequency components [36–38]. Therefore, to extract meaningful information from multi-frequency EEG signals, decomposition techniques have been highly preferred [36–39]. As evident from Table A.3, decomposition techniques like discrete wavelet transform (DWT), tunable Q wavelet transform (TQWT), flexible analytic wavelet transform (FAWT), dual-tree complex wavelet transform (DT-CWT), EMD, VMD, and MVMD have been extensively used to extract desired frequency bands and instantaneous information about time and frequency [40–55]. The features extracted from the sub-components of these decomposition methods are further used for classification using ML-based techniques. In addition, due to high temporal resolution and presence of multi-frequency components, transforming time-series EEG to TFR using STFT, smoothed pseudo-Wigner Ville distribution (SPWVD), S-trans form, Wigner Ville distribution (WVD), and quadratic time-frequency distribution (QTFD) have also been preferred [56–64]. The TFR obtained from these techniques is combined with DL models like CNN for emotion recognition. The analysis shows that the highest accuracy of 100% has been achieved for valence, arousal, and dominance classification on the DREAMER dataset [54]. Similarly, an accuracy of 99.56%, 99.67%, and 99.55% for arousal, dominance, and valence has been achieved on the DEAP dataset using LOSO CV [54]. Nonlinear decomposition techniques provide an effective representation of EEG signals, due to which it has obtained the highest classification accuracy [54]. In addition, extraction of TFR from EEG signals using SPWVD and TOR-based on S-T in combination with CNN has resulted in an accuracy of 93.01% and 94.58% for discrete emotion classification on private EEG datasets [58,61]. Thus, the summary of Table A.3 reveals that the decomposition techniques with ML models and the combination of TFR with DL models have resulted in the highest performance, in terms of accuracy, for emotion recognition.

12.2. Takeaways from ECG-based emotion recognition studies

ECG signals are quasi-stationary with a high signal-to-noise ratio (SNR) compared to EEG signals. Therefore, direct feature extraction can help to extract representative and meaningful information from ECG signals. Thus ECG-based studies have preferred direct feature extraction in terms of NLF, STSF, rhythmic, TDF, and FDF [53,65–75]. Since ECG is quasi-stationary and contains mixed frequency components, wavelet, and EMD-based decomposition have also attained high accuracy [65,76–78]. SVM and KNN-based ML techniques have successfully classified different emotions due to their ability to draw accurate boundaries between distinct emotion classes. Due to the rhythmic nature and high SNR of ECG signals, DL techniques have extracted representative features, which has resulted in high system performance [53,73,74,79–83]. The highest accuracy of 100% has been achieved for discrete emotion classification using rhythmic features clubbed with SVM classifier on a private dataset [66]. In another study, researchers obtained 100% accuracy for classifying discrete emotions as well as the classification of valence and arousal [77]. The authors in [77] used wavelet-based features and a probabilistic neural network (PNN) classifier. The combination of CNN and LSTM has resulted in an accuracy of 98.73% and 90.5% using DL models on public AMIGOS and DREAMER datasets [82].

12.3. Takeaways from GSR-based emotion recognition studies

Like EEG and ECG signals, GSR signals are also non-stationary and nonlinear. Therefore, extracting meaningful and representative information from them is preferred. Features are extracted in the form of NLF, STSF, entropy, TDF, FDF, and/or rhythms [53,67,84–90]. Decomposition techniques based on EMD and wavelets were explored, due to their ability to extract crucial characteristics required for the classification of emotions [77,85,91–93]. Extraction of features or decomposition makes it easy for classifiers to draw decision boundaries for different emotions. Therefore, ML models like SVM and KNN have yielded very high classification accuracy. Also, transforming a signal to another domain and applying DL models has been effective for emotion recognition [53,82,94,95]. The highest accuracy of 100% has been obtained for features based on Poincare plots (PCP), Lyapunov exponent (LE), and approximate entropy (APEN) using PNN classifier on the DEAP dataset [87]. Similarly, the study based on EMD and TDF using SVM classifier has also achieved the perfect classification of emotions on a private dataset [91]. In addition, statistical features [89], wavelet analysis [77], NLF [90], and DWT [93] have also achieved high accuracy for emotion detection. Thus, direct extraction of STSF, entropy, TDF, FDF, and NLF can provide accurate emotion representation using GSR signals. Also, wavelets and decomposition techniques can extract discriminative characteristics from GSR signals for emotion recognition.

12.4. Takeaways from ET-based emotion recognition studies

The summary of Table A.6 reveals that NLF, STSF, and FDF of ET signals can provide a better emotion representation [96–99]. In addition, DL models can also extract representative features, which has resulted in high accuracy [96,97,99]. The highest accuracy of 92% has been achieved with STSF and deep multi-layer perceptron (DMLP) classifier for valence state on the eSEE-d public dataset. However, more analysis is still required to confirm these findings. Also, validation of the model using holdout CV is prone to over-fitting thus, may not yield the same performance during LOSO or k-FCV.

12.5. Takeaways from speech-based emotion recognition studies

Speech signals have prosody, non-stationary, language specificity, and are context dependent. In addition, speech signals are non-station ary, and some of them have periodicity [100]. Therefore, the representation of speech in spectral features using MFCC, MFC, STFT, and WT has been effective for emotion recognition [101–112]. Statistical features have provided a discriminant representation of speech signals, due to which it has obtained the effective classification of emotions [103,109,113,114]. The speech-based emotion recognition has attained higher accuracy when CNN models have been clubbed with spectral representation including simultaneous time and frequency information [107,109–112,114–117]. As mentioned earlier, due to prosody and context dependency features of speech, attention-based CNN, LSTM, and BiLSTM have also remained effective in speech-based emotion classification [110,118–121]. The highest accuracy of 100% has been achieved on EMO-DB and CASIA public datasets using MFCC features and linear discriminant analysis classifier [105].

12.6. Takeaways from facial image-based emotion recognition studies

Facial images for emotion recognition involves facial characteristics. Therefore, techniques like face extraction, geometric features, texture features, and binary patterns have been the most effective [122–132]. Similarly, as emotions are recognized using images, CNN models have been the most effective decision-making models due to their ability to extract spatio-temporal characteristics. Attention-modules with CNN have also been proven effective to detect face geometry for emotion recognition [129,133–136]. The highest accuracy of 100% has been achieved on JAFFE public image dataset using convolutional features and the CNN model [137]. Similarly, an accuracy of 99.36% has been obtained on the CK+ dataset using the CNN model [138]. An accuracy of 99.59% has been achieved on the MMI dataset using optical flow spatial–temporal feature (OFSTF) clubbed with the CNN model [136].

12.7. Overall summary of automated emotion recognition system

The graphical representation of the automated emotion recognition for all the modalities used in the current review is shown in Fig. 16. The summary reveals that physiological (EEG, ECG, ET, and GSR) and physical (speech) signals extensively explored feature extraction. Nonlinear decomposition is mostly used for extracting meaningful information from EEG, ECG, and GSR signals. Physiological signals (EEG, ECG, GSR, and ET) contain multi-components, that are nonstationary and nonlinear nature. Therefore, decomposition techniques like EMD, VMD, and wavelet transform (DWT, TQWT, FAWT, and others) provide effective representation of various emotional states. Also, nonlinear and statistical features from the multi-components of EEG, ECG, GSR, and ET have yielded the most representative characteristics for emotion recognition. Frequency-domain features for speech and direct feature extraction for ET are widely used. Deep features have been used the most for facial images. The use of Mel-frequency cepstrum coefficients for speech and face extraction for images has provided the discriminative features for emotion recognition. Finally, for decision-making, the SVM-based ML

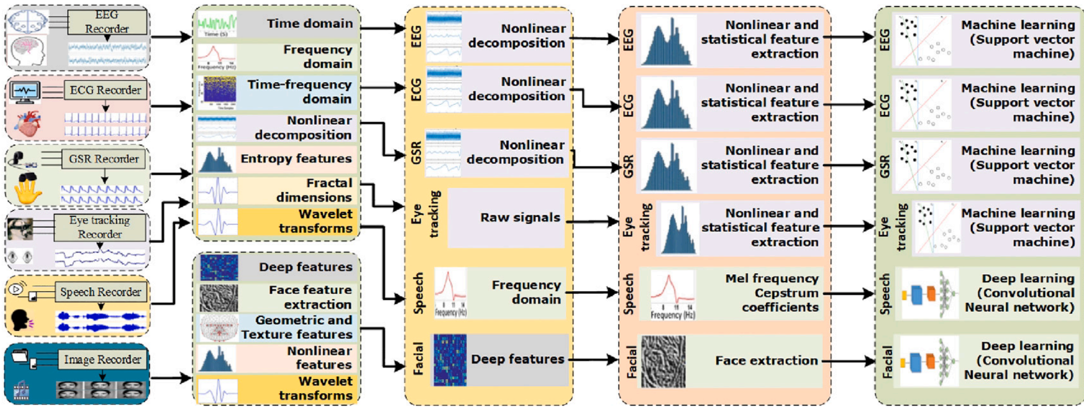

Fig. 16. Graphical representation and summary of included modalities emotion recognition.

modality has been the most effective and preferred classifier for EEG, ECG, GSR, and ET signals. The review studies suggest that, for speech signals and facial images, decision-making using CNN-based DL models may result in the highest performance. The CNN models have inbuild convolutional layers, which reduces the high dimensionality of images without losing its information. Therefore, CNN models can effectively extract features from images and learn to recognize patterns, making them well suited for emotion recognition. Also, feature extraction and transformation techniques are widely used for time-series input signals, including EEG, ECG, GSR, speech, and ET. The overall analysis has revealed that information fusion helps to improve the system's performance. The study shows that fusion of EEG with ECG/GSR, and ECG with GSR or by fusing different features provided higher accuracy than due to single modality [71,82,84,88,92,93]. Therefore, feature- and sensor-level fusion obtained from multiple sources can be the better option for emotion recognition.

The overall summary of the modalities covered in our review study for emotion recognition with their strengths and weaknesses/future recommendations are shown in Table 2. It is noteworthy to mention that the summary is drawn based on our observations from the papers included in the systematic review.

13. Challenges

After a thorough investigation of automated emotion recognition systems, we have identified potential challenges in existing studies. The major challenges in automated emotion recognition systems are listed below:

13.1. Datasets

Most of the datasets used for emotion recognition are available publicly. However, the majority of them have been utilized to their maximum capacity, resulting in the highest classification accuracy. In addition, the available datasets have been acquired with a single modality i.e., either for EEG, ECG, ET, GSR, speech, or facial images. Therefore, there still exists a research gap in analyzing emotion recognition using multiple modalities from the same subject. Also, the lack of availability of public emotion datasets for healthcare, brain-computer interfaces, and other applications limits such analysis.

13.2. Adaptive analysis and classification

The physiological and physical signals are nonlinear, multi-frequency components, and vary spontaneously [39,139,140]. Accurate and effective analysis of such signals can be accomplished with feature extraction and decomposition techniques. But, to extract meaningful information from such signal, tuning of parameters is required [46,47]. However, our review study shows that few studies have been explored for an adaptive analysis of these signals. These data-driven models have been tested on private EEG datasets [46,47]. Therefore, adaptive analysis can be used for extracting representative information from EEG, ECG, ET, GSR, and/or speech signals. Similarly, for classification, ML and/or DL models require extensive tuning of hyper-parameters for optimal performance. Empirical and pre-fixed settings of tuning hyper-parameters may not yield desired performance.

13.3. Lack of generalization

The acquisition of physiological and physical signals has been done with different systems. The varying system specifications and acquisition time, results in the generation of sequences of different lengths. Our review analysis shows that research studies for emotion recognition using EEG, ECG, GSR, and speech signals have been analyzed with different segment lengths. The changing duration of signals to be analyzed may not yield desired performance. The lack of information and generalization on the selection of signal length makes it difficult for the stakeholders to trust the decision given by the developed models.

13.4. Lack of trust in automated decision-making

It is difficult to trust the outcome of such an automated system, especially when the findings contrast or conflict with previous knowledge or expectations. As a result, stakeholders, specialists, and physicians are hesitant to rely on existing models to make decisions. This is why, despite several significant technological improvements in signal processing, feature engineering, and AI, these models fail to gain the faith of experts. Furthermore, there are few occasions when real-time support systems for decision-making are used in research facilities. This is due to the inability of present emotion identification techniques to explain the predictions provided by decision support systems. To create confidence in automated systems, the models must explain the judgments made by the automated system to experts.

14. Future recommendations and research directions

Our review study has identified unresolved research challenges in current emotion recognition systems. Future research should concentrate on innovative ways to increase our understanding of numerous modalities and applications. The following explains the potential directions for future research directions.

Table 2
Summary of emotion recognition studies included in the review with their strengths, limitations, and future directions.

Modality	Strengths	Future recommendations
EEG	• Well studied • Comprehensive analysis of TDF, FDF, STSF, NLF, and TFR features • Explored ML and DL models • Attained maximum accuracy • Validation of multiple datasets • Availability of public datasets	• Uncertainty in performance • Exhaustive use of available datasets • Tested on cleaned and pre-processed data • Lack of adaptivity • Lack of explainability • Non-uniformity in EEG segment length selection • Limited usage of hyperparameter tuning • Limited usage of fusion techniques
ECG	• Well studied • Attained maximum accuracy • Validation of multiple datasets • Availability of public datasets	• Uncertainty in performance • Exhaustive use of available datasets • Tested on cleaned and pre-processed data • Lack of adaptivity • Explored mainly ML models • Lack of explainability • Non-uniformity in ECG segment length selection • Limited usage of hyperparameter tuning • Limited usage of fusion techniques
GSR	• Well studied • Attained maximum accuracy • Validation of multiple datasets • Availability of public datasets	• Uncertainty in performance • Exhaustive use of available datasets • Tested on cleaned and pre-processed data • Lack of adaptivity • Explored mainly ML models • Lack of explainability • Non-uniformity in GSR segment length selection • Limited usage of hyperparameter tuning • Limited usage of fusion techniques
ET	• Usage of datasets generated from different stimuli • Usage of direct feature extraction • Generation of simple models	• Uncertainty in performance • Limited public datasets • Lack of adaptivity • Lack of explainability • Limited usage of hyperparameter tuning
Speech	• Comprehensive analysis of feature extraction techniques • Models are generated and validated on multiple datasets • Availability of public datasets • Usage of ML and DL techniques	• Non-data driven models • Frequency-domain feature centric • Uncertainty in performance • Lack of adaptivity • Lack of explainability • Limited usage of hyperparameter tuning
Facial images	• Models are generated and validated on multiple datasets • Availability of public datasets • Usage of ML and DL techniques	• Non-data driven models • Uncertainty in performance • Lack of adaptivity • Lack of explainability • Limited usage of hyperparameter tuning

14.1. Application of human emotion recognition

Emotion recognition covers many applications, including brain-computer interfaces, robotics, and healthcare. However, with the recent technological advancements and rise in electronic gadget usage, emotion recognition can help to accelerate in various fields. Some of them are listed below:

14.1.1. Detection and monitoring of medical conditions

Human emotion can reveal crucial information for health conditions and numerous disorders. Research has been conducted on variations of emotions in Parkinson's disease (PD), schizophrenia, Alzheimer's disease (AZD), attention deficit hyperactivity disorder (ADHD), Autism spectrum disorder (ASD), epilepsy, and depression. Changes in the emotional states have been witnessed during PD. Variations in emotional states during PD were observed using facial expressions, speech, and EEG signals [141–144]. Few researches have also been conducted on variations in emotions during schizophrenia. Studies have observed that facial expressions, auditory, and EEG signals measure emotional states in schizophrenia [145–147]. Reading the Mind in the Eyes Test, facial expression, eye blinks, and contextual features shows variation in emotions in AZD [148–151]. Facial expressions, text, EEG signals, and emoji-based studies have shown emotional changes in depression [152–154]. Changes in the emotional states in ADHD from facial processing and social cognition have been studied [155–157]. The study of emotions from facial expressions, video games, speech signals, and EEG has been used to detect ASD [158–161]. Similarly, facial expressions and social cognition can be detected in seizures and epilepsy [162,163]. Therefore, a thorough investigation can be explored for the detection of various disorders from emotions. However, very few studies are available due to the lack of availability of public datasets. Fig. 17 shows an automated emotion-based physiological and neurological disorder detection system.

14.1.2. Children health

The study and analysis of emotions in children can also play a crucial role in their health monitoring. Studies revealed that emotional development and regulation can be crucial in children with dyslexia [164–166], depression [167,168], anxiety [169,170], and autism [171–173]. Therefore, the study of facial expressions, speech, and physiological signals can be used to detect autism, depression, anxiety, and dyslexia. Also, emotion recognition can play a crucial role to teach children with autism and dyslexia.

14.1.3. Environmental health studies

Another potential application of human emotions recognition is in environmental health studies. It is known that the physical environment can have an influence on emotions and, ultimately, affect

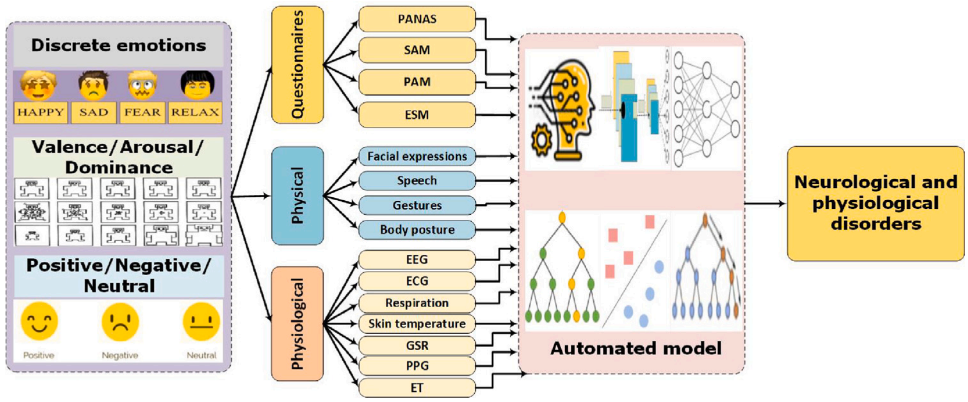

Fig. 17. Overview of the emotion-based automated disorder detection system.

mental health. For instance, environmental stressors (e.g. air and noise pollution) can be linked to a series of negative emotions, e.g., annoyance, anger, disappointment, dissatisfaction, helplessness, anxiety, and agitation [174,175]. However, a deep understanding of the mental effects due to various environmental factors has been limited by, among others, the difficulty in measuring complex emotional states in humans.

14.1.4. Human-robot interactions

The rise in AI has boosted the development of human-modeled machines. The applications of human emotions have attracted researchers to investigate human-machine interfaces and sentimental analysis. Human-machine interfaces can infer and understand human emotions, making them more successful in human interactions; the models should be able to interpret human emotions and adapt their behavior appropriately, resulting in an acceptable reaction to those sentiments.

14.1.5. Patience assistance

Emotion can be pivotal in patient monitoring and assistance. Effective analysis of emotion can help to sense and detect loneliness, mood variations, and suicidal cues.

14.1.6. Driving assistance

Emotion recognition can also be used to detect driver's fatigue. Facial expressions, eye movements, and/or EEG can be used in real-time driver fatigue monitoring.

14.1.7. Education

Accurate and effective analysis of emotions can help to study students' level of satisfaction in education.

14.1.8. Marketing

A camera with AI systems in shopping malls can be used to read the real-time emotions of customers, which may be used for marketing.

14.1.9. Recruitment

Automated analysis of an automatic emotion recognition system can be used for recruitment. Analysis of emotions during interviews can be used to monitor the stress level of candidates.

14.1.10. Business models

People show numerous expressions and thoughts about various products. Retailers can use customers' thoughts and feeling to improve the in-store experience. Its purpose is to compare data from typical satisfaction evaluations to data from emotion recognition technologies to determine whether emotion recognition can offer a complete picture or perhaps replace satisfaction measurements [176,177].

14.1.11. E-learning

We have seen a drastic increase in electronic gadgets and internet services usage since the COVID era. Online environments and virtual classrooms can provide uninterrupted learning, and emotion detection technology assists in identifying students' emotional and understanding levels in real-time. This information may be used to create class content based on children's diverse learning capacities [178,179].

14.2. Generation of multimodal public datasets

Human emotions can be studied to detect various disorders, but such studies have not been explored to their maximum capacity. One reason is that lack of available and diverse datasets. Therefore, the development of such datasets and making them available freely to the research community can boost emotion-based physiological disorder detection. Also, instead of focusing on a uni-modal dataset, the development of a multi-modal dataset can enrich and explore higher possibilities for extended emotion recognition studies. Accessibility and authorization criteria must be simple and fast so that specialists can avoid waiting for a long period. Data collecting methodologies and processes should be made accessible so that other research organizations can replicate them and gather more data for study.

14.3. Development of wearable emotion recognition systems

Physical signals, including speech, gesture, facial expression, text, posture, etc. are susceptible to false positives. Such signals can be voluntarily changed resulting in false emotion classifications [47,180]. Our review analysis shows that EEG signals have been widely preferred for emotion recognition, but usage of numerous EEG sensors for acquisition introduce system complexity. Emotions have also been detected using ECG signals, which use only three channels [65,67,81, 181]. Thus, the usage of ECG signals for emotion recognition is advantageous in terms of the number of sensors and high signal-to-noise ratio [39]. The human central nervous system is built in such a way that alterations in one organ influence another. As a result, the brain-heart relationship, brain-eyes interaction, and brain–heart–eyes–muscle communication may be critical and beneficial in analyzing changes in many organs [39,182]. Photoplethysmography (PPG) signals provide a better representation of brain-heart interaction [183,184]. PPGs have the advantage of not requiring specific setups or many electrodes for signal collection. The sensors are attached to wristwatches, fingers, or other wearable devices that are more accessible, less expensive, and more practical than other physiological signals.

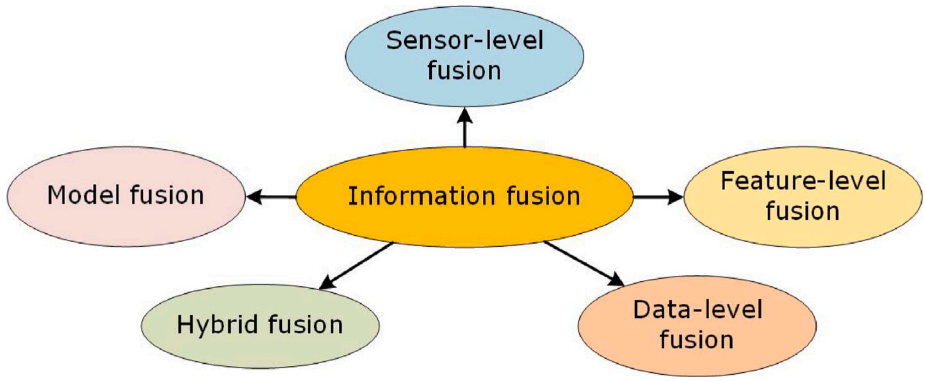

Fig. 18. Taxonomy of information fusion.

14.4. Distributed learning models

Huge volumes of data are being produced due to expansion in AI and big data technology. The AI is booming due to the extraction of valuable information from a large volume of data and has the potential for the advancement of human society. The current automated emotion recognition models are developed using centralized ML. However, data acquired from different regions can have subjective changes, geographical variations, and instrumental differences, which may provide dynamic variations in the performance of traditional ML models. Also, traditional ML uses centralized learning model, which suffers privacy issues and communication load. To overcome this federated learning (FL) can be used. The main goal of FL is to move model training from a central server to client devices, allowing many client datasets to work together on model training while protecting data privacy and lowering communication costs. It uses a "data stationary, model moving" learning mode compared to centralized learning's "model stationary, data moving" method [185,186].

14.5. Information fusion

Information fusion, also known as data fusion, is a process that combines, integrates, and analyzes data from numerous sources to provide a more detailed and precise representation of the desired phenomenon. The primary purpose of information fusion is to extract subtle information from diverse often imperfect data sources, resulting in enhanced decision-making, increased comprehension, and improved performance in a variety of applications. There are various levels and types of information fusion as shown in Fig. 18 and discussed below:

14.5.1. Sensor-level fusion

This level includes integrating unprocessed data from each sensor without any processing or analytics. It is used to enhance data quality, decrease noise, and deal with missing or incorrect data from certain sensors [187].

14.5.2. Feature-level fusion

This level combines data from several sources that have been pre-processed and important characteristics extracted before being integrated [188]. This method seeks to minimize the data's dimensionality and establish a single feature representation for subsequent analysis.

14.5.3. Model fusion

Model fusion or model ensemble technique increases predictive model performance and generalization [189]. Model fusion is based on the notion of combining predictions from various independent models in a manner to get a final, more robust prediction. Combining the capabilities of different models can frequently result in improved overall prediction precision while reducing the risk of over-fitting.

14.5.4. Data-level fusion

Data-level fusion includes both sensor-level and feature-level fusion [190]. It entails integrating raw data from numerous sensors and then extracting important characteristics from the combined data.

14.5.5. Hybrid fusion

Hybrid level combines two or more level of fusion techniques e.g., feature-level and decision-level fusions. Suppose the classification of physical signals is accomplished using feature-level fusion with a single decision-making classifier. On the other hand, analysis of physiological signals can be accomplished using decision-level fusion. The final decision is generated by integrating feature-level and decision-level fusions to generate the desired performance [191,192].

14.6. Application of explainability

Explainable Artificial Intelligence (XAI) is a strategy for developing AI systems that tries to give explicit and intelligible explanations for the AI model's decisions. The decision-making in AI models, such as SVM, may be complicated to comprehend. This lack of transparency creates issues, particularly in essential applications such as healthcare, where knowing the logic behind AI choices is critical for trust, accountability, and safety. These issues are addressed by XAI approaches, which make AI models more visible and interpretable. Clients, programmers, and stakeholders can understand how the AI system arrived at a certain outcome by giving human-readable explanations. The explanations provided by XAI approaches are transparent, which is critical for model trust, bias and fairness, debugging, and improvement. For ML models, techniques include feature visualization (learning patterns in the data), rule-based models (explicit rules for decision-making), local explanations (local explanations focus on explaining specific predictions or decisions), and feature importance (LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations)) [193]. For CNN, heat-maps (class activation map (CAM)) including Grad-CAM, Grad-CAM++, SMOOTHGRAD, U-CAM, Eigen-CAM, and Score-CAM have been used for explanations [184]. An overview of traditional ML models and XAI models is shown in Fig. 19.

14.7. Uncertainty quantification

Uncertainty quantification (UQ) is a collection of mathematical and computational tools for assessing and characterizing uncertainty in computational models, simulations, and data analysis [194–196]. Understanding the uncertainty associated with the results is critical in many scientific and technical domains because precise predictions are dependent on it [194]. Uncertainty can arise from various sources including model formulation (from simplifications, assumptions, or approximations), input data (noise, missing data, or measurement errors), model parameters (fixed parameters), approximations, and initial and boundary conditions [197]. The sources of uncertainty can be measured using UQ, which aims to address the following questions:

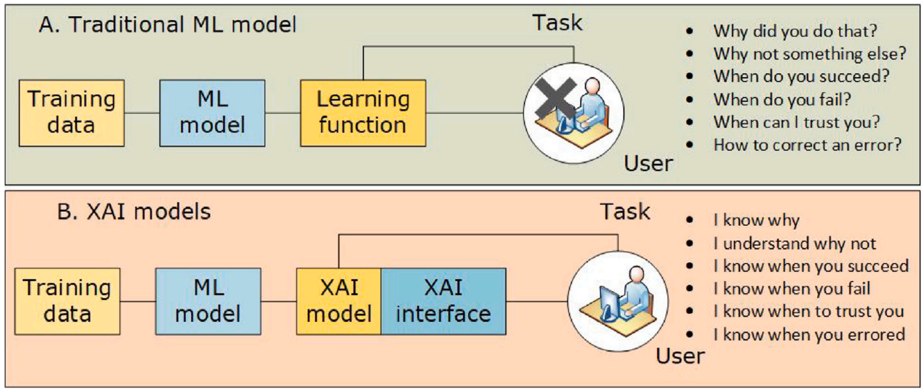

Fig. 19. Illustrative representation of XAI model (A) Traditional ML model and (B) XAI model with explanations.

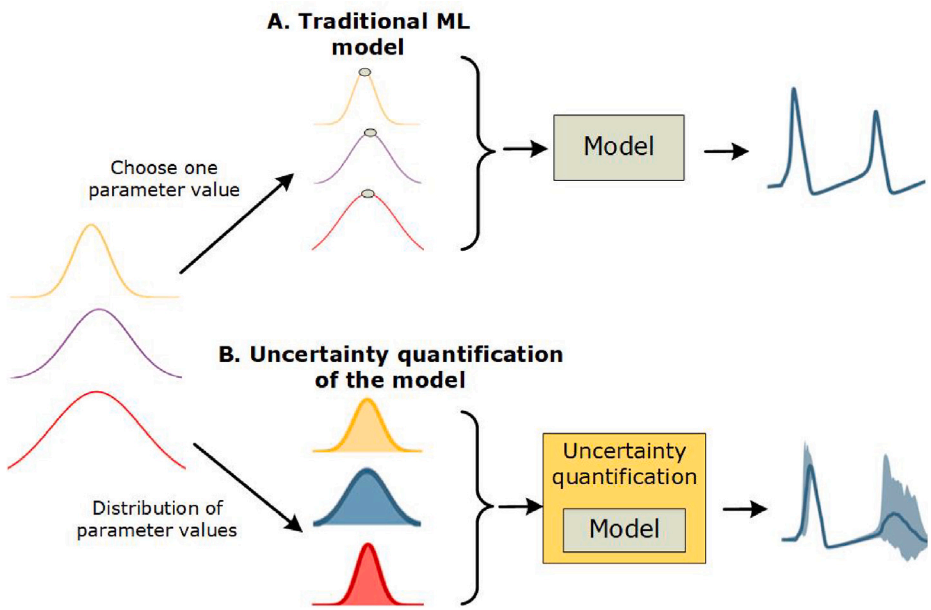

Fig. 20. Illustrative uncertainty quantification of deterministic model (A) Traditional model with fixed parameter setting and (B) An UQ of the model with distributed parameter settings.

- How do uncertainties in input parameters affect the model's predictions?
- What are the sources of uncertainty in the model and its input parameters?
- How reliable are the model predictions?
- How can we improve the model and reduce uncertainties?

UQ entails estimating probability distributions, statistical moments (mean, variance, etc.), and confidence intervals that indicate the uncertainty associated with the results. Some well-known techniques used for UQ involve Bayesian inference, variance-based methods, Monte Carlo methods, probabilistic collocation, ensemble modeling, and bootstrapping [194,198]. The graphical overview of uncertainty quantification of a deterministic model is shown in Fig. 20.

15. Conclusion

Emotion recognition is crucial in multiple fields, including healthcare, E-learning, online shopping, etc. Our paper has presented a fine-grained analysis of human emotions. This comprehensive analysis of emotion recognition systems shows that decomposition techniques provide insight information that extracts representative features from physiological signals. The SVM-based ML decision-making has been proven the most effective and preferred emotion recognition model. The ability of DL models to automatically extract and classify deep features is gaining popularity and has been increasing in the usage of CNN models. Our review analysis shows that feature fusion and data fusion help to improve the overall system performance. Hence, information fusion should be used in future emotion recognition models. Emotions can be very helpful in certain healthcare applications, such as Alzheimer's disease, Parkinson's disease, depression, and schizophrenia detection, as well as in e-learning, market analysis, and human–robot interactions. However, these fields have seen limited research in human emotion recognition systems, due to the lack of available public datasets. Therefore, our review recommends developing and providing accessible public datasets for increasing the applications of human emotions research studies. The review shows that deep learning models have gained popularity over traditional ML. Therefore, combination of hybrid DL techniques using CNN, autoencoders, LSTM, and transformer models may be adopted for emotion recognition applications. Also, accurate versatile models can be designed using federated meta learning to train the automated systems on different datasets for a particular application. Finally, we highlight the importance of model explainability and uncertainty quantification in emotion recognition to strengthen the trust and overall impact of AI models.

Table A.3
Summary of emotion recognition studies using EEG signals included in the review.

Ref.	Year	Sub.	Dataset	Dataset name	Status	Length	NCH	Emotion (Classes)	Feature extraction	Classification	Validation	Accuracy (%)	Decision type
[199]	2019	20	AV	–	Private	10 s	1	Discrete (4)	DF with NLF	LSSVM	10 FCV	90.63	ML
[40]	2019	20	AV	–	Private	10 s	1	Discrete (4)	TQWT with STSF	ELM	10 FCV	87.1	ML
[41]	2022	23	AV	DREAMER	Public	–	14	V/A (9)	DWT and EMD with STSF	Ensemble ML	10 FCV	93.79 (A) 94.5 (V)	ML
		15	AV	SEED	Public	–	12	Pos/Neg/Neu (3)				81.39 (A) 79.71 (V)	
		20	Music	MUSEC	Public	–	27	V/A (2)				81.96 (A) 82.27 (V)	
		43	AV	INTERFACES	Public	–	4	V/A (3)				59.67 (A) 59.67 (V)	
[200]	2014	16	Image	–	Private	30 s	64	Discrete (5)	NLF	QDA	8 FCV	47.5	ML
[201]	2018	32	AV	DEAP	Public	12 s	32	V/A (2)	LF and NLF	SVM	LOSO CV	59.06	ML
		15	AV	SEED	Public	12 s	62	Pos/Neg (2)				83.33	
[42]	2022	32	AV	DEAP	Public	–	32	V/A (2)	VMD	DNN	Holdout	61.25 (A) 62.5 (V)	DL
[43]	2017	32	AV	DEAP	Public	4 s	10		DWT with ENT	KNN	10 FCV	86.75	ML
[56]	2021	32	AV	DEAP	Public	3 s	32	V/A/D (3)	PCC	CNN	Holdout	70.25 (A) 74.92 (V)	DL
								V/A (2)				74.92 (A) 78.22 (V)	
[202]	2019	32	AV	DEAP	Public	63 s	32	V/A/D (3)	MBFM	CapsNet	10 FCV	68.28 (A) 66.73 (V) 67.25 (D)	DL
[203]	2019	32	AV	DEAP	Public	1 s	32	V/A (2)	PSD	LSTM	10 FCV	74.38 (A) 81.1 (V)	DL
[204]	2020	15	AV	SEED	Public	12 s	62	Pos/Neg/Neu (3)	PSD	DGCNN	LOSO CV	79.95	DL
		23	AV	DREAMER	Public	–	14	V/A/D (9)				84.54 (A) 86.23 (V) 85.02 (D)	
[205]	2020	32	AV	DEAP	Public	2 s	8	V/A (2)	Windowing	CNN	LOSO CV	72.81	DL
		15	AV	SEED	Public	1.5 s	8	Pos/Neg (2)				86.56	
		11	AV	LUMED	Public	0.6 s	8	Valence (2)				81.8	
[44]	2020	20	AV	–	Private	–	16	V/A (2)	EMD with NLF	SVM	Holdout	74.88 (A) 82.63 (V)	ML
[57]	2020	15	AV	SEED	Public	1 s	32	Pos/Neg/Neu (3)	STFT	CNN	Holdout	90.59	DL
		32	AV	DEAP	Public	1 s	32	V/A (9)				82.84	
[45]	2016	32	AV	DEAP	Public	3 s	32	V/A (4)	EMD and SaENT	SVM	10 FCV	94.98 (BC) 93.20 (MC)	ML
[46]	2021	20	AV	–	Private	10 s	1	Discrete (4)	AVMD with NLF	ELM	10 FCV	97.24	ML
[47]	2020	20	AV	–	Private	10 s	1	Discrete (4)	ATQWT with STSF	LSSVM	10 FCV	95.7	ML
[58]	2021	20	AV	–	Private	10 s	16	Discrete (4)	SPWVD	CNN	Holdout	93.01	DL
[206]	2022	15	AV	SEED	Public	–	62	Pos/Neg/Neu (3)	DE	RGNN	LOSO CV	85.3	DL
		15	AV	SEED IV	Public		62	Discrete (4)				73.84	
[207]	2015	15	AV	SEED	Public	1 s	62	Pos/Neg/Neu (3)	DE	DBN	Holdout	86.08	DL
[59]	2019	27	AV	MAHNOB-HCI	Public	10 s	32	Valence	PSD and NetP	GELM	10 FCV	68	ML
		15	AV	SEED	Public	10 s	62	Pos/Neg/Neu (3)	DE and NetP			88	
[48]	2019	15	AV	SEED	Public	1 s	1	Pos/Neg/Neu (3)	FAWT and IPF	RF	10 FCV	92.84	ML
		32	AV	DEAP	Public	1 s 1 s	1 1	Discrete (2) Discrete (4)				80.64 72.07	
[208]	2019	32	AV	DEAP	Public	1 s	32	Discrete (2)	PSD	CNN	10 FCV	100	DL
[49]	2020	15	AV	SEED	Public	5 s	62	Pos/Neg/Neu (3)	DT-CWT	SRU	Holdout	83.13	DL
[60]	2022	32	AV	DEAP	Public	1 s	32	V/A (9)	STFT and DE	LSTM	LOSO CV	90.91 (V) 90.87 (A)	DL
		15	AV	SEED	Public	1 s	62	Pos/Neg/Neu (3)				90.92	
		37	AV	CMEED	Public	1 s	30	V/A (2)				94.21 (V) 88.03 (A)	
[209]	2021	32	AV	DEAP	Public	1 s	32	V/A (9)	Windowing	DFR	10 FCV	97.69 (V) 97.53 (A)	DL
		23	AV	DREAMER	Public	1 s	14	V/A/D (9)				89.03 (A) 90.41 (V) 89.89 (D)	
[210]	2023	32	AV	DEAP	Public	6.25 s	1	V/A (9)	Windowing	ACRNN	10 FCV	93.72 (V) 93.38 (A)	DL
		23	AV	DREAMER	Public	9.76 s	1	V/A/D (9)				97.98 (A) 97.93 (V) 89.23(D)	
[61]	2020	20	AV	–	Private	10 s	1	Discrete (4)	TOR-based on S-TF	AlexNet (CNN)	Holdout	94.58	DL
[62]	2018	32	AV	DEAP	Public	4 s	23	V/A/D (9)	QTFDs	SVM	10 FCV	87 (V) 88.4 (A)	ML
[211]	2019	15	AV	SEED	Public	–	62	Pos/Neg (2)	NLF	SVM	LOSO CV	89	ML
		32	AV	DEAP	Public	–	32	V/A/D (9)				72	
[212]	2020	10	AV	–	Private		14	Discrete (3)	PSD and WE ENT	RVM	10 FCV	91.18	ML
[63]	2021	23	AV	DREAMER	Public	–	14	V/A (2)	THFM	CNN	10 FCV	88.20 (V) 90.43 (A)	DL
		15	AV	SEED	Public	–	62	Pos/Neg (2)				88.45 (V)	
		32	AV	DEAP	Public	–	32	V/A (2)				76.61 (V) 77.72 (A)	
		40	AV	AMIGOS	Public	–	14	V/A (2)				87.39 (V) 90.54 (A)	
[50]	2021	28	CG	GAMEEMO	Public	3.74 s	1	Discrete (4)	TQWT and FFP	SVM	10 FCV	99.82	ML

(*continued on next page*)

Table A.3 (*continued*).

Ref.	Year	Sub.	Dataset	Dataset name	Status	Length	NCH	Emotion (Classes)	Feature extraction	Classification	Validation	Accuracy (%)	Decision type
[51]	2022	23	AV	DREAMER	Public	2 s	4	V/A/D (3)	MVMD and ResNet18	SVM	10 FCV	99.03 (A) 95.17 (D) 94.53 (V)	ML
		40	AV	AMIGOS	Public		4	V/A/D (3)				96.68 (A) 97.45 (D) 95.58 (V)	
[52]	2017	32	AV	DEAP	Public	5 s	8	V/A (2)	EMD and STSF	SVM	LOSO CV	69.10 (V) 71.99 (A)	ML
[213]	2022	15	AV	SEED IV	Public	4 s	62	Discrete (4)	NL, PSD, and DEC	GFIL	LOSO CV	79.17	ML
[214]	2020	32	AV	DEAP	Public	10 s	14	V/A/D (3)	PSD, ENT, WT, and FD	SVM	5 FCV	78.96 (A) 77.60 (D) 77.62 (V)	ML
[215]	2018	32	AV	DEAP	Public	–	18	V/A (2)	MEMD and STSF	KNN	LOSO CV	51.01 (A) 67 (V)	ML
[64]	2020	15	AV	SEED	Public	1 s	62	Pos/Neg/Neu (3)	STFT, DE and rhythms	CNN	5 FCV	91.68	DL
[216]	2016	32		DEAP	Public	4 s	19	Discrete (4)	FFT and rhythms	SVM	10 FCV	59.13	ML
[53]	2019	23	AV	MPED	Private	1 s	62	Pos/Neg/Neu (3) Discrete (2) Discrete (7)	PSD, NLF, and NL DEC	LSTM	Holdout	72.36 78.79 42.1	DL
[67]	2018	58	AV	ASCERTAIN	Public		8	V/A (2)	STSF	NB	LOSO CV	60 (A) 61 (V)	ML
[84]	2020	21	AV	–	Private	–	4	Discrete (4)	STSF	KNN	10 FCV	75	ML
[217]	2021	23	AV	DREAMER	Public	10 s	4	V/A/D (3)	Rhythms	Deep CNN	10 FCV	98.82 (A) 98.99 (D) 98.56 (V)	DL
		32	AV	DEAP	Public	10 s	19	Discrete (4)				98.45 (A) 98.69 (D) 98.91 (V)	
		23	AV	DASPS	Public	10 s	14	V/A (2)				57.14	
[54]	2021	23	AV	DREAMER	Public	–	4	V/A/D (3)	TQWT with PP and STSF	SVM	LOSO CV	100 (A) 100 (D) 100 (V)	ML
		32	AV	DEAP	Public	–	19	Discrete (4)				99.56 (A) 99.67 (D) 99.55 (V)	
		28	CG	GAMEEMO	Public	–	1	Discrete (4)				100	
[218]	2022	25	VR	VREED	Public	4 s	64	Pos/Neg (2)	DE	SVM	Holdout	76.22	ML
[55]	2022	165	Image	ICBrainDB	Public	3 s	128	Discrete (4)	TQWT with HOG, and LBP	KNN	10 FCV	90.77	ML
[82]	2020	40	AV	AMIGOS	Public	1 s	3	V/A(4)	Filtering	CNN-LSTM	Holdout	98.8 (Fused) 74.65 (EEG)	DL
		23	AV	DREAMER	Public		3	V/A/D (4)				90.5 (Fused) 48.54 (EEG)	
[71]	2021	20	AV	–	Private	–	14	V/A (4)	STSF and rhythms	SVM	10 FCV	82.63 (V) 74.88 (A) EEG 85.38 (V) 77.52 (A) Fused	ML

Table A.4
Summary of emotion recognition studies using ECG signals included in the review.

Ref.	Year	Sub.	Dataset	Dataset name	Status	Length	NCH	Emotion (Classes)	Feature extraction	Classification	Validation	Accuracy (%)	Decision type
[65]	2021	40	AV	AMIGOS	Public	20 s	3	V/A (2)	WST, TDF, and FDF	Ensemble	10 FCV	88.8 (A) 88.9 (V)	ML
[66]	2017	69	Video Image AV	–	Private	20 s	3	Discrete (2)	Rhythmic features	SVM	10 FCV	100 100 100	ML
[67]	2018	58	AV	ASCERTAIN	Public		3	V/A (2)	NLF and rhythmic features	Naïve Bayes	LOSO CV	60 (V) 59 (A)	ML
[68]	2017	69	Video Image AV	–	Private	20 s	3	Discrete (5)	Rhythmic features	SVM	10 FCV	73.8 62.4 72.8	ML
[69]	2014	60	AV	–	Private	3.6 s	3	Discrete (6)	NLF	FKNN	Holdout	92.87	ML
[76]	2014	30	AV	–	Private	–	3	Discrete (6)	EMD with HHT EMD EMD with DFT	KNN	Holdout	40.14 29.92 52.11	ML
[70]	2020	–	Music	Augsburg university database	Public	–		Discrete (4)	Rhythmic features	FHMM	Holdout	95	ML
[79]	2022	23	Image	–	Private	20 s	3	V/A (2)	Filtering	CNN	10 FCV	76.19 (V) 80.95 (A)	DL
		23	AV	DREAMER	Public	20 s	3	V/A (2)				97.56 (V) 96.34 (A)	
[53]	2019	23	AV	MPED	Private	1 s	3	Pos/Neg/Neu (3) Discrete (2) Discrete (7)	FFT and NLF	LSTM	Holdout	53.2 55.24 25.1	DL
[80]	2023	23	AV	DREAMER	Public	1 s	3	V/A (5)	–	CNN with CBAM	Holdout	87.7 (V) 87.4 (A)	DL
		15	AV	WESAD	Public	1 s	3	Affect state (4)	–			97.5	
		58	AV	ASCERTAIN	Public	1 s	3	V/A(7)	–			78.7 (V) 76.3 (A)	
[219]	2017	24	AV	MAHNOB-HCI	Public	–	3	V/A(2)	HRV	SVM	–	60.83 (V) 65.73 (A)	ML
[81]	2021	15	AV	–	Private		3	Discrete (4)	Filtering and CWT	CNN-LSTM	LOSO CV	71.67	DL
[86]	2021	58		ASCERTAIN	Public	4 s	3	V/A (4)	Heart rate variability	SVM	10 FCV	78.32 (V) 76.83 (A)	ML
[71]	2021	20	AV	–	Private	–	3	V/A (2)	STSF and rhythmic features	SVM	10 FCV	76.65 (V) 70.15 (A) EEG-ECG 85.38 (V) 77.52 (A)	ML
[72]	2015	27	Audio	–	Private	88 s	3	V/A (2)	NLF and LF	QDA	LOSO CV	84.72 (V) 84.26 (A)	ML
[220]	2020	86	AV	BioVid Emo DB	Public	68 s	3	Discrete (5)	Filtering	SVM	Holdout	80.89	ML
[73]	2022	23	AV	DREAMER	Public	–	3	V/A/D (–)	TDF, FDF, and NLF	CNN	10 FCV	95.16 (V) 85.56 (A) 77.54 (D)	DL
[82]	2020	40	AV	AMIGOS	Public	1 s	3	V/A (4)	Filtering and segmentation	CNN-LSTM	Holdout	98.8 (Fused) 98.73 (ECG)	DL
		23	AV	DREAMER	Public	1 s	3	V/A/D (4)				90.8 (Fused) 90.5 (ECG)	
[74]	2023	24	AV	MAHNOB-HCI	Public	15 s	3	V/A (2)	MRF and HRV	BiLSTM	10 FCV	83.61 (A) 78.28 (V)	DL
[77]	2017	11	Music	–	Private	–	16	Discrete (5)	WDEC and DCT	PNN	Holdout	100 (Discrete) 100 (V) 100 (A)	ML
[75]	2020	61	Music	–	Private	60 s	3	Discrete (4)	TDF, FDF, and NLF	LS-SVM	LOSO CV 10 FCV	68.1 (LOSO) 80.51 (10 FCV)	ML
[83]	2022	40	AV	AMIGOS	Public	20 s	3	V/A (4)	Windowing	SL CNN	10 FCV	88.9 (A) 87.5 (V)	DL
		23	AV	DREAMER	Public	60 s	3	V/A (4)				85.9 (A) 85 (V)	
		25	AV	SWELL	Public	60 s	3	Discrete (4)				93.3 (Stress) 96.7 (A) 97.3 (V)	
		15	AV	WESAD	Public	5 s	3	Discrete (4)				96.9	
[78]	2019	25	AV	–	Private	20 s	2	Discrete (4)	Rhythmic and EMD	Extra tree	10 FCV	70.09	ML

CRediT authorship contribution statement

Smith K. Khare: Conceptualization, Methodology, Writing – original draft, Validation, Editing. **Victoria Blanes-Vidal:** Validation, Reviewing and editing. **Esmaeil S. Nadimi:** Validation, Reviewing and editing. **U. Rajendra Acharya:** Conceptualization, Validation, Reviewing and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article

Appendix A. Summary of the emotion recognition studies

See Tables A.3–A.8.

Appendix B. Summary of the emotion datasets

See Tables B.9–B.14.

Appendix C. Abbreviations

See Table C.15.

Table A.5
Summary of emotion recognition studies using GSR signals included in the review.

Ref.	Year	Sub.	Dataset	Dataset name	Status	Length	Emotion (Classes)	Feature extraction	Classification	Validation	Accuracy (%)	Decision type
[77]	2017	11	Music	–	Private	–	Discrete (5)	WDEC and DCT	PNN	Holdout	99.59 (Discrete) 99.52 (V) 99.66 (A)	ML
[84]	2020	21		–	Private	–	Discrete (4)	STSF	KNN	10 FCV	72.61 (GSR) 79.76 (Fused)	ML
[85]	2017	32	AV	DEAP	Public	3 s	V/A/D (2)	DWT and EMD based STSF	RF	10 FCV	89.29 (V) 81.81 (A)	ML
[86]	2021	58	AV	ASCERTAIN	Public	4 s	V/A (4)	TDF and FDF	SVM	10 FCV	60.05 (V) 55.63 (A) Fused features 76.81 (V) 75.24 (A)	ML
[87]	2020	32	AV	DEAP	Public	3 s	V/A/D (4)	PCP, LE, and APEN	PNN	5 FCV	100 (V) 100 (A)	ML
[94] [91] [221]	2019 2020 2018	100 37 39	AV AV AV	MDSTC dataset – –	Private Private Private	1 s – –	Discrete (6) Discrete (3) Discrete (3)	Spectrogram EMD and TDF filtering	CNN-LSTM SVM SVM	Holdout 10 FCV Holdout	Recall: 80.07 100 75.65	DL ML ML
[88]	2016	30	AV	–	Private	–	Discrete (4)	STSF	RF	10 FCV	75 (Fused features)	ML
[95]	2022	62 32	AV AV	MERTI-Apps DEAP	Public Public	1.1 s 1.1 s	V/A (2) V/A (3)	Windowing and filtering	1D AE	Holdout	81.33 (A) 80.25 (V) 79.18 (A) 74.84 (V)	DL
[89]	2021	34 15	Audio AV	– WESAD	Private Public	– –	Discrete (4) Discrete (4)	STSF	ANN	10 FCV	99.4 99.4	ML
[92]	2016	11	Music	–	Private	10 s	V/A (3) Discrete (5)	DWT	PNN	Holdout	95.10 (Dis) 97.90 (V) 95.80 (A) Fused 100 (Dis) 100 (V) 100 (A)	ML
[90]	2017	35	Music	–	Private	10 s	Discrete (4)	NLF	LSSVM	5 FCV	99.98	ML
[222]	2022	58	AV	ASCERTAIN	Public		V/A (4)	–	SVM	–	99.67	ML
[93]	2016	11	Music	–	Private	–	V/A (3) Discrete (5)	DWT with matching pursuit	PNN	Holdout	69.93 (Dis) 81.82 (V) 79.02 (A) Fused 99.64 (Dis) 99.51 (V) 99.44 (A)	ML
[53]	2019	23	AV	MPED	Private	1 s	Pos/Neg/Neu (3) Discrete (2) Discrete (7)	FFT and NLF	LSTM	Holdout	60.24 63.37 31.19	DL
[67]	2018	58	AV	ASCERTAIN	Public	–	V/A (2)	NLF and rhythmic features	NB	LOSO CV	68 (V) 66 (A)	ML
[82]	2020	40	AV	AMIGOS	Public	1 s	V/A (4)	Filtering and segmentation	CNN-LSTM	Holdout	98.8 (Fused) 63.67 (GSR)	DL

Table A.6
Summary of emotion recognition studies using ET signals included in the review.

Ref.	Year	Sub.	Dataset	Dataset name	Status	Length	Emotion (Classes)	Feature extraction	Classification	Validation	Accuracy (%)	Decision type
[96]	2021	16	Image	–	Private	–	Discrete (4)	FFT and STFT with FDF	DGCNN	Holdout	87.97	DL
[97]	2023	48	Video	eSEE-d	Public	–	Discrete (4)	STSF	DMLP	10 FCV	92 (V) 81 (A)	DL
[223]	2021	10	Virtual reality	–	Private	–	Discrete (4)	–	SVM	LOSO CV	59.19	ML
[98]	2019	10	Video	–	Private	–	Discrete (4)	–	–	–	–	
[224]	2020	30	Video	–	Private	–	Discrete (3)	NLF	SVM	LOSO CV	80	ML
[225]	2021	10	Image	–	Private	–	Discrete (8)	NLF and FDF	DGNN	Holdout	88.1	DL

Table A.7
Summary of emotion recognition studies using SPEECH signals included in the review.

Ref.	Year	Sub.	Dataset	Dataset name	Status	Length	Emotion (Classes)	Feature extraction	Classification	Validation	Accuracy (%)	Decision type
[101]	2020	24	AV	RAVDESS	Public	10 ms	Discrete (8)	MFCC and MS	CNN	Holdout	78.2	DL
[102]	2020	7	Audio	LDC	Public		Discrete (4)	MFCC and LPCC	SVM	Holdout	90.08	ML
[103]	2020	24	AV	RAVDESS	Public	10 ms	Discrete (8)	DWT, MFCC, and STSF	Decision Tree	Holdout	85	ML
[113]	2020	10	AV	IEMOCAP	Private	–	Discrete (4)	STSF	1D CNN	5 FCV	86.1	DL
		24	Acted	RAVDESS	Public	10 ms	Discrete (8)				71.61	
		10	Audio	EMO-DB	Public	–	Discrete (7)				64.3	
[226]	2014	10	Audio	EMO-DB	Public	–	Discrete (7)	Spectral analysis	KNN	Holdout	50	ML
[104]	2019	330	AV	AFEW	Public	40 ms	Discrete (7)	FFT and MSG	CNN	Holdout	60.59	DL
[105]	2022	10	Audio	EMO-DB	Public	2 s	Discrete (7)	MFCC and BLS	LDA	Holdout	100	ML
		4	Audio	CASIA	Private	2 s	Discrete (6)				100	
[106]	2015	10	Audio	EMO-DB	Public	–	Discrete (6)	Fourier parameters and MFCC	SVM	Holdout	88.88	ML
		4	Audio	CASIA	Private	–	Discrete (6)				79	
		16	Audio	EESDB	Public	–	Discrete (4)				50.67	
[107]	2019	10	AV	IEMOCAP	Private	–	Discrete (4)	SG and MFCC	CNN	5 FCV	73.6	DL
[108]	2019	10	Audio	EMO-DB	Public	25 ms	Discrete (7)	MFCC and SCF	Bagged tree	10 FCV	92.45	ML
		24	AV	RAVDESS	Public	25 ms	Discrete (8)				75.69	
		10	Audio	IITKGP-SEHSC	Private	25 ms	Discrete (8)				84.11	
[118]	2019	42	AV	eNTERFACE	Public	–	Discrete (6)	–	LSTM	Holdout	89.6	DL
		4	Audio	CASIA	Private	–	Discrete (6)				92.8	
			AV	GEMEP	Private	–	Discrete (12)				57	
[227]	2019	4	Audio	CASIA	Private	–	Discrete (6)	FFT	DNN-SVM	Holdout	72.92	DL
[119]	2020	24	AV	RAVDESS	Public	0.5 s	Discrete (8)	clustering	BiLSTM	Holdout	77.02	DL
		10	AV	IEMOCAP	Private	0.5 s	Discrete (4)				72.25	
		10	Audio	EMO-DB	Public	0.5 s	Discrete (7)				85.57	
[120]	2021	10	Audio	EMO-DB	Public	–	Discrete (7)	PSF and EE	SVM	7 FCV	89.65	ML
		24	AV	RAVDESS	Public	–	Discrete (8)				82.59	
		14	AV	SAVEE	Public	–	Discrete (7)				77.74	
[109]	2018	4	Audio	CASIA	Private	–	Discrete (6)	MFCC and STSF	BEL	Holdout	90.28	DL
		14	AV	SAVEE	Public	–	Discrete (7)				76.4	
		51	Audio	FAU	Private	–	Discrete (7)				71.05	
[115]	2022	10	AV	IEMOCAP	Private	10 ms	Discrete (4)	SIT	CNN (ResNet152)	Holdout	82.25	DL
		10	Audio	EMO-DB	Public	10 ms	Discrete (7)			5 FCV	96.14	
[116]	2019	10	Audio	EMO-DB	Public	–	Discrete (7)	STFT	CNN	Holdout	77.33	DL
[228]	2021	2	Audio	TESS	Public	2–3 s	Discrete (6)	EMD with ENT	LDA	10 folf CV	93.3	ML
[110]	2021	10	AV	IEMOCAP	Private	20 ms	Discrete (4)	MFCC, ZCR, spectral spread, and centroid	LSTM	Holdout	72.5	DL
[121]	2019	10	Audio	EMO-DB	Public	20 ms	Discrete (7)	PSCF	ELM	Holdout	91.02	ML
		14	AV	Amritaemo Arabic database	Private	20 ms	Discrete (6)				86.98	
[229]	2017	10	AV	IEMOCAP	Private	25 ms	Discrete (4)	Log FT	CNN	LOSO CV	64.78	DL
[230]	2022	18	Audio	Turkish SER dataset	Private	5 s	Discrete (3)	TQWT and SLP	SVM	10 FCV	96.41	ML
		45	Audio	English SER dataset	Private	5 s	Discrete (3)				94.97	
[114]	2019	10	AV	IEMOCAP	Private	–	Discrete (4)	STFT and SG	CNN	5 FCV	81.75	DL
		24	AV	RAVDESS	Public	–	Discrete (8)				79.5	
[111]	2020	24	AV	RAVDESS	Public	–	Discrete (8)	MEL spectrogram	MLP	–	83.8	DL
		10	AV	IEMOCAP	Private	–	Discrete (4)		CNN-SVM		81.3	
		10	Audio	EMO-DB	Public	–	Discrete (7)		SVM		95.1	
		14	AV	SAVEE	Public	–	Discrete (7)		SVM		82.1	
[117]	2018	31	AV	BAUM	Public	10 ms	Discrete (12)	LMSG	CNN	LOSO CV	44.61	DL
		10	Audio	EMO-DB	Public	10 ms	Discrete (7)				87.31	
		42	AV	eNTERFACE	Public	10 ms	Discrete (6)				79.25	
		8	AV	RML	Public	10 ms	Discrete (6)				75.34	
[231]	2018	4	Audio	CASIA	Private		Discrete (6)	PSF	ELM	LOSO CV	89.6	ML
[112]	2021	24	AV	RAVDESS	Public	–	Discrete (8)	Spectrum and spectrogram	CNN	10 FCV	85	DL
		10	Audio	EMO-DB	Public	–	Discrete (7)				95	
		14	AV	SAVEE	Public	–	Discrete (7)				82	
[232]	2021	24	AV	RAVDESS	Public	–	Discrete (8)	TQWT with TSP	SVM	10 FCV	87.43	ML
		10	Audio	EMO-DB	Public	–	Discrete (7)				90.09	
		14	AV	SAVEE	Public	–	Discrete (7)				84.79	
		6	Audio	EMOVO	Public	–	Discrete (7)				79.08	

Table A.8
Summary of emotion recognition studies using IMAGE signals included in the review.

Ref.	Year	Sub.	Dataset name	Status	No. of images	Emotion (Classes)	Feature extraction	Classification	Validation	Accuracy (%)	Decision type
[122]	2022	70 201	KDEF CK+	Public Public	4900 3368	Discrete (7) Discrete (7)	FLC	SVM RF	Holdout	85 97.86	ML
[233]	2022	201 10	CK+ JAFFE	Public Public	3368 213	Discrete (7) Discrete (7)	GM-WLBP, GLCM and GLRM	CNN-LSTM	Holdout	91.42 92.85	DL
[123]	2022	337 –	CMU Multi-PIE AffectNet	Public Public	750K+ 1M	Discrete (5) Discrete (8)	Face extraction using MTCNN	MTCNN	Holdout	90 90	DL
[138]	2022	10 118	JAFFE CK+	Public Public	213 3150	Discrete (7) Discrete (7)	Normalization, scaling, and augmentation	CNN	Holdout	95.65 99.36	DL
[124]	2023	10 – ≈450 000 19	JAFFE FER2013 AffectNet MMI	Public Public Public Public	213 35,887 1M 4756	Discrete (7) Discrete (7) Discrete (8) Discrete (6)	RetinaFace	CNN	Holdout	98.44 74.64 62.78 99.02	DL
[234]	2020	– ≈35,887 –	RAF-DB FER2013 ExpW	Public	15 539 35,953 91 793	Discrete (7) Discrete (7) Discrete (7)	Reinforcement learning	CNN	Holdout	72.84 72.35 50.61	DL
[125]	2019	123 10 52	CK+ JAFFE MUG	Public Public Public	309 213 304	Discrete (7) Discrete (7) Discrete (6)	Geometric and texture features	DAGSVM	–	91.11 63.33 82.28	ML
[235]	2021	–	CK+	Public	918	Discrete (7)	–	MobileNet CNN	Holdout	98.5	DL
[236]	2019	97 10	CK+ JAFFE	Public Public	8150 213	Discrete (7) Discrete (7)	Gaussian normalization	CNN with RB	Holdout	93.24 95.23	DL
[126]	2019	450 000 –	AffectNet RAF-DB	Public	220K+ 15 539	Discrete (8) Discrete (7)	MTCNN	Generater CAE	Holdout	74.8 81.83	DL
[133]	2021	123 – 10 –	CK+ FER2013 JAFFE FERG	Public Public Public Public	593 35,887 213 55,767	Discrete (7) Discrete (7) Discrete (7) Discrete (7)	SIFT, HOG, and LBP	Attention CNN	Holdout	98 70.02 92.8 99.3	DL
[127]	2020		SAVEE	Public	480	Discrete (7)	Facial graphs	ANN	Holdout	90	ML
[237]	2020	95 100 270	SFEW BU-3DFE CMU Multi-PIE	Public Public Public	700 21 000 7655	Discrete (7) Discrete (7) Discrete (6)	GGPI	GAN	Holdout	27.24 81.95 92.09	DL
[128]	2019	123 10	CK+ JAFFE	Public Public	593 213	Discrete (7) Discrete (7)	Appearance and geometric features	CNN	10 FCV	96.46 91.27	DL
[238]	2019	– –	FER2013 LFW	Public Public	35,887 13 000	Discrete (7) Discrete (7)	Normalization, equalization, and image edge	CNN	Holdout	88.56 (fused)	DL
[129]	2020	10 123 – 35 80	JAFFE CK+ FER2013 NCUFE Oulu-CASIA	Public Public Public Private Public	213 593 35,887 26,950 2880	Discrete (7) Discrete (7) Discrete (7) Discrete (7) Discrete (6)	Cropping and facial feature extraction	CNN with attention	Holdout	98.52 98.9 75.82 94.33 94.63	DL
[239]	2020	27 337 1573	CK+ CMU Multi-PIE NIST	Public Public Public	450 750K+ 3248	Discrete (7) Discrete (5) –	Expressional vector	CNN	Holdout	85 78 96	DL
[134]	2019	–	AffectNet	Public	300K	Discrete (8)	Position level features	BiRNN	Holdout	–	DL
[240]	2021	123 10 18	CK+ JAFFE FEEDTUM	Public Public Public	593 213 –	Discrete (7) Discrete (7) Discrete (7)	MSWGT	SVM	–	98.9 97.1 95.8	ML
[241] [135] [242]	2016 2020 2023	20 – –	– Downloaded FER2013	Private Private Public	700 23,164 35,887	Discrete (7) Discrete (8) Discrete (7)	BOWT – Gray scale	SVM ResNet-MldrNet CNN	10 FCV 5 FCV Holdout	96.77 67.75 54	ML DL DL
[136]	2019	67 123 88	RaFD CK+ MMI	Public Public Public	1608 593 5042	Discrete (8) Discrete (7) Discrete (9)	OFSTF	CNN with inception	Holdout	99.17 98.38 99.59	DL
[130]	2020	67	Turkey student DB	Private	–	Discrete (7)	Facial features	–	–	–	
[137]	2021	70 10	KDEF JAFFE	Public Public	4900 213	Discrete (7) Discrete (7)	Convolutional-based features	CNN (DenseNet121)	Holdout 10 FCV	98.78 (Holdout) 96.51 (10 FCV) 100 (Holdout) 99.52 (10 fold CV)	DL
[131]	2015	– 10	CK+ JAFFE	Public Public	329 183	Discrete (6) Discrete (6)	Salient facial patches	SVM	10 FCV	94.09 91.79	ML
[243]	2017	2,64,683	SocialMedia	Public	2 mil.	Discrete (10)	Generic and special features	SVM	Holdout	–	ML
[132]	2022	– 123	UNBC-McMaster CK+	Public Public	88 427 593	Discrete (2) Discrete (7)	Aligned face crop	LSTM	LOSO CV	90.3 97.2	DL

Table B.9
Details of the EEG datasets used for emotion recognition.

Ref.	Subjects	Dataset	Dataset name	Status of dataset	Recorder	NCH	Samp. Freq.	Type of classification	Evoked emotions	Self-assessment
[199]	20	AV	–	Private	EEG traveler	24	256	Discrete emotions	Happy, fear, sad, and relax	SAM
[244]	23	AV	DREAMER	Public	Emotive EPOC	14	128	V/A/D	Amusement, surprise, excite- ment, happiness, calmness, anger, disgust, fear, and sadness	SAM
[207, 245]	15	AV	SEED	Public	ESI NeuroScan System	62	200	Pos/Neu/Neg	Positive, neutral, and negative	PQES, FAM, UL
[246]	20	Music	MUSEC	Public	g.USBamp	62	1200	V/A	Favored Melody, favored Song, non-favored Melody, non-favored Song	–
[247]	32	AV	DEAP	Public	Biosemi ActiveTwo	32	128	V/A/D/liking	LALV, HALV, LAHV, and HAHV	SAM
[248]	43	AV	INTER-FACES	Public	OpenBCI	8	250	V/A	Happiness, Excitement, and Fear	SAM
[200]	16	Images	–	Private	g.USBamp	64	512	V/A/D	Happy, curious, angry, sad, and quiet	SAM
[249]	11	AV	LUMED	Public	Neuro-electrics Enobio 8	8	500	V (Neg and Pos)	Positive, neutral, and negative	–
[44]	20	AV	–	Private	Emotiv Epoc	16	–	V/A	Happy, relaxed, angry, sad and disgust	SAM
[250]	15	AV	SEED IV	Public	ESI NeuroScan System	62	200	Discrete emotions	Happiness, sadness, fear, and neutral	PANAS
[251]	27	AV	MAHNOB-HCI	Public	Biosemi Active II s	32	1024	Valence	Amusement, joy, neutral, sadness, fear, and disgust	SAM
[252, 253]	37	AV	CMEED	Public	NuAmps 40	32	128	V/A	Positive, neutral, and negative	SAM
[212]	10	AV	–	Private	Emotiv EPOC	14		Discrete emotions	Happiness, neutral, and sadness	SAM
[254]	40	AV	AMIGOS	Public	Emotiv EPOC	14	128	V/A/D	Neutral, Disgust, Happiness, Surprise, Anger, Fear and Sadness	SAM
[255]	28	Games	GAMEEMO	Public	EMOTIV EPOC	14	128	Discrete emotions	Funny, Boring, Horror, Calm	SAM
[256]	23	AV	MPED	Private	ESI NeuroScan System	62	1000	Discrete emotions	Joy, funny, anger, fear, sadness, disgust, and neutral	PANAS, SAM, and DES
[257]	58	AV	ASCER-TAIN	Public	Neuro Sky EEG	8	32	V/A	Arousal, Valence, Engagement Liking, Familiarity	SAM
[258]	23	AV	DASPS	Public	Emotiv EPOC	14	128	V/A	LALV, HALV, LAHV, and HAHV	SAM and HAM-A
[259]	25	VR	VREED	Public	Wireless EEG device	64	1000	Neg and Pos	Neg and Pos	–
[260]	165	Image	ICBrainDB	Public	Brain Products actiChamp	128	1000	Discrete emotions	Happy, angry, sad, and neutral	–
[71]	20	AV	–	Private	Emotive EPOC	14	128	V/A	LALV, HALV, LAHV, and HAHV	SAM

Table B.10
Details of the ECG datasets used for emotion recognition.

Ref.	Subjects	Dataset	Dataset name	Status of dataset	Recorder	NCH	Samp. Freq.	Type of classification	Evoked emotions	Self-assessment
[254]	40	AV	AMIGOS	Public	SHIMMER	3	256	V/A/D	Neutral, Disgust, Happiness, Surprise, Anger, Fear and Sadness	SAM
[66]	69	Image Video AV	–	Private	Radio frequency type device	3	960	Discrete emotions	Happy, neutral, and anger	–
[257]	58	AV	ASCER-TAIN	Public	–	3	–	V/A	Arousal, Valence, Engagement Liking, Familiarity	SAM
[69]	60	AV	–	Private	Power Lab data Acquisition	3	1000	Discrete	Happiness, sadness, fear, disgust, surprise and neutral	SAM
[261]	–	Music	Augsburg university database	Public	–	–	256	Discrete	Joy, anger, sadness, and pleasure	–
[79]	23	Image	–	Private	MP150 system	3	1000	V/A	Calm, relaxed, content, glad, delighted, bored, annoyed, depressed, others, gloomy, afraid, angry, excited	SAM
[244]	23	AV	DREAMER	Public	SHIMMER	3	256	V/A/D	Amusement, surprise, excite- ment, happiness, calmness, anger, disgust, fear, and sadness	SAM
[256]	23	AV	MPED	Private	BIOPAC System	3	250	Discrete emotions	Joy, funny, anger, fear, sadness, disgust, and neutral	PANAS, SAM, and DES
[262]	15	AV	WESAD	Public	RespiBAN Professional	3	700	Affect state	Neutral, stress, amusement	PANAS, STAI, and SAM
[251]	24	AV	MAHNOB-HCI	Public	Biosemi active II	3	256	Valence	Amusement, joy, neutral, sadness, fear, and disgust	SAM
[81]	15	AV	–	Private	ECG monitor (PC-80B)	3	154	Discrete emotions	Relax, scary, disgust, and joy	SAM
[71]	20	AV	–	Private	–	3	128	V/A	Happy, relaxed, angry, sad, and disgusted	SAM
[72]	27	Audio	–	Private	BIOPAC inc.	3	500	V/A	Low-medium valence and medium-high valence	SAM
[263]	86	AV	BioVid Emo DB	Public	Nexus-32	3	512	Discrete emotions	Amusement, sadness, anger, disgust and fear	SAM
[77]	11	Music	–	Private	PowerLab	16	400	Discrete emotions	Peacefulness, happiness, sadness, rest, and scary	–
[75]	61	Music	–	Private	NeXus-10	3	2048	Discrete emotions	Joy, tension, sadness, and peacefulness	GEMS-9
[264]	25	AV	SWELL	Public	TMSI MOBI device	3	2048	Affect state	Valence, arousal, and stress	SAM
[78]	25	AV	–	Private	SpikerShield Heart	2	1000	Discrete emotions	Joy; sadness; pleasure; anger; fear; and neutral	SAM

Table B.11
Details of the GSR datasets used for emotion recognition.

Ref.	Subjects	Dataset	Dataset name	Status of dataset	Recorder	Samp. Freq.	Type of classification	Evoked emotions	Self-assessment
[77]	11	Music clips	–	Private	PowerLab	400	Discrete emotions	Peacefulness, happiness, sadness, rest, and scary	–
[84]	21		–	Private	Shimmer	256	Discrete emotions	Happy, angry, sad, and relaxed	SAM
[247]	32	AV	DEAP	Public	Biosemi ActiveTwo	128	V/AD/liking	LALV, HALV, LAHV, and HAHV	SAM
[94]	100	AV	MDSTC	Private	Customized physiological sensor device	200	Discrete emotions	Surprise, angry, disgust, happy, fear, and sad	SAM
[91]	37	AV	–	Private	Bluno Nano, DFRobot	500	Discrete emotions	Amusement, sadness, and neutral	SAM
[257]	58	AV	ASCER-TAIN	Public	–	256	V/A	Arousal, Valence, Engagement Liking, Familiarity	SAM
[221]	39	AV	–	Private	–	–	Discrete	Positive, negative, and neutral	PANAS
[88]	30	AV	–	Private	BIOPAC MP150	1000	Discrete	Neutral, sadness, fear and pleasure	SAM
[265]	62	AV	MERTI-Apps	Public	BIOPAC MP150	1000	V/A	Happy, angry, sad, and scared	SAM
[89]	34	Audio	–	Private	MySignals hardware	260	Discrete	Relax, stressed, partially stressed, and happy	–
[262]	15	AV	WESAD	Public	RespiBAN Professional	700	Affect state	Neutral, stress, amusement	PANAS, STAI, and SAM
[90]	35	Music	–	Private	PowerLab	400	Discrete emotions	Happiness, sadness, peacefulness, and scary	–
[256]	23	AV	MPED	Private	BIOPAC System	250	Discrete emotions	Joy, funny, anger, fear, sadness, disgust, and neutral	PANAS, SAM, and DES
[254]	40	AV	AMIGOS	Public	Shimmer	256	V/A/D	Neutral, Disgust, Happiness, Surprise, Anger, Fear, and Sadness	SAM

Table B.12
Details of the ET datasets used for emotion recognition.

Ref.	Subjects	Dataset	Dataset name	Status of dataset	Recorder	Samp. Freq.	Type of classification	Evoked emotions	Self-assessment
[96]	16	Image	–	Private	Tobii pro eye-tracker	600	Discrete emotions	Calm, happy, nervous, and sad	–
[97]	48	Video	eSEE-d	Public	Pupil Labs	240	Discrete emotions	Anger, disgust, sadness and tenderness	SAM
[223]	10	Virtual reality	–	Private	Pupil Labs		Discrete emotions	–	–
[98]	10	Video	–	Private	Tobii TX300 eye-tracker	300	Discrete emotions	Joy, love, inspiration, and serenity	–
[224]	30	Video	–	Private	EyeTribe	60	Discrete emotions	Pleasant, neutral, and unpleasant	SAM
[225]	10	Image	–	Private	Eye-Tracking	600	Discrete emotions	Angry, disgust, fear, sad, expect, happy, surprised, trust	SAM

Table B.13
Details of the SPEECH datasets used for emotion recognition.

Ref.	Subjects	Dataset	Dataset name	Status of dataset	Recorder	Samp. Freq.	Type of classification	Evoked emotions	Self-assessment
[266]	24	Audio video	RAVDESS	Public	Rode NTK	48 K	Discrete emotions	Calm, happy, sad, angry, fearful, surprise, and disgust expressions	SAM
[267]	7	Audio	LDC	Public	WAVES+	22.05 K	Discrete emotions	Disgust, panic, anxiety, hot anger, cold anger, despair, sadness, elation, happy, interest, boredome, shame, pride, and contempt	–
[268]	10	Audio video	IEMOCAP	Private	VICON motion capture system	48 K	Discrete emotions	Anger, happiness, sadness, neutrality	SAM
[269]	10	Audio	EMO-DB	Public	Tascam DA-P1	16 K	Discrete emotions	Disgust, sadness, happiness, boredom, fear, neutral, and anger	–
[270]	330	Audio video	AFEW	Public	–	–	Discrete emotions	Happiness, surprise, anger, disgust, fear, sadness and neutral	–
[271]	4	Audio	CASIA	Private	RODE K2	16 K	Discrete emotions	Angry, happy, fear, sadness, surprise and neutral	–
[272]	16	Audio	EESDB	Public	Cooleditpro	–	Discrete emotions	Angry, disgust, fear, happy, neutral, sad, and surprise	–
[273]	10	Audio	IITKGP-SEHSC	Private	SHURE dynamic cardioid microphone C660N	16 K	Discrete emotions	Happy, Sad, Angry, Sarcastic, Fear, Neutral, Disgust, and Surprise	–
[274]	42	Audio video	eNTERFACE	Public	D1/DV PAL	48 K	Discrete emotions	Anger, Disgust, fear, happiness, sadness, and surprise	–
[275]		Audio video	GEMEP	Private	SENNHEISER	41 K	Discrete emotions	Amusement, pride, joy, relief, interest, pleasure, hot anger, panic fear, despair, irritation, anxiety, sadness	SAM
[276–278]	14	Audio video	SAVEE	Public	Surrey audio-visual expressed emotion database	44.1 K	Discrete emotions	Anger, Disgust, Fear, Happiness, Sadness,Surprise, and Neutral	–
[279]	51	Audio	FAU	Private	SHURE UHF-serie	16 K	Discrete emotions	Angry, Emphatic, Positive, Neutral, and Rest	SAM
[280]	2	Audio	TESS	Public	–	–	Discrete emotions	Anger, disgust, fear, happiness, pleasant surprise, sadness, and neutral	–
[121]	14	Audio video	Amritaemo Arabic database	Private	Adobe Audition software	16 K	Discrete emotions	Anger, happy, sad, disgust, surprise, and neutral	SAM
[230]	18	Audio	Turkish SER dataset	Private	–	–	Discrete emotions	Positive, negative, and neutral	–
[230]	45	Audio	English SER dataset	Private	–	–	Discrete emotions	Interesting, boring, and neutral	–
[281]	31	Audio video	BAUM	Public	–	48 K	Discrete emotions	Happiness, sadness, fear, anger, disgust, confusion, boredom, and interest	–
[282]	8	Audio video	RML	Public	–	44.1 K	Discrete emotions	Anger, disgust, fear, joy, sadness, and surprise	–
[283]	6	Audio	EMOVO	Public	Marantz PMD670	48 K	Discrete emotions	Neutral, Anger, Disgust, Fear, Happiness, Sadness, Surprise	SAM

Table B.14
Details of the IMAGE datasets used for emotion recognition.

Ref.	Subjects	Dataset	Dataset name	Status of dataset	Type of classification	Evoked emotions	Self-assessment
[284]	70	KDEF	Public	4900	Discrete emotions	Angry, Fearful, Disgusted, Sad, Happy, Surprised, and Neutral	–
[285]	210	CK+	Public	8150	Discrete emotions	Angry, Contempt, Disgust, Fear, Happy, Sadness, and Surprise	FACS
[286]	10	JAFFE	Public	213	Discrete emotions	Happiness, sadness, surprise, anger, disgust, fear, and neutral	–
[287, 288]	337	CMU Multi-PIE	Public	750K+	Discrete emotions	Neutral, smile, surprise, squint, disgust, and scream	–
[289]	–	AffectNet	Public	1M	Discrete emotions	Neutral, happy, sad, surprise, fear, disgust, anger and contempt	SAM
[290]	–	FER2013	Public	31K+	Discrete emotions	Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral	–
[291]	88	MMI	Public	5042	Discrete emotions	Anger, fear, and sadness, happiness, surprise and disgust	FACS
[292, 293]	–	RAF-DB	Public	29 672	Discrete emotions	Disgust, happy, sad, anger, fear, and surprise	SAM
[294]	–	ExpW	Public	91 793	Discrete emotions	Angry, disgust, fear, happy, sad, surprise, and neutral	–
[295] [296]	52 –	MUG FERG	Public Public	304 55K+	Discrete emotions Discrete emotions	Disgust, happy, sad, anger, fear, and surprise Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral	FACS FACS
[276–278]	–	SAVEE	Public	480	Discrete emotions	Anger, Disgust, Fear, Happiness, Sadness, Surprise, Neutral	–
[297]	95	SFEW	Public	700	Discrete emotions	Anger, Disgust , Fear, Happiness , Sadness, Surprise, and Neutral	SAM
[298]	100	BU-3DFE	Public	21K	Discrete emotions	Anger, Disgust , Fear, Happiness , Sadness, Surprise, and Neutral	SAM
[299]	5749	LFW	Public	13 233	Discrete emotions	Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral	SAM
[129]	35	NCUFE	Private	26,950	Discrete emotions	Anger, disgust, fear, happiness, sadness, surprise, and neural	–
[300]	80	Oulu-CASIA	Public	2880	Discrete emotions	Anger, disgust, fear, happiness, sadness, and surprise	–
[301]	1573	NIST	Public	3248	–	–	–
[302]	18	FEEDTUM	Public	–	Discrete emotions	Neutral, anger, disgust, fear, happiness, sadness and surprise	–
[135, 303]	–	Downloaded	Private	23,164	Discrete emotions	Happy, sadness, surprise, anger, disgust, fear, and neutral	–
[304]	67	RaFD	Public	1608	Discrete emotions	Anger, disgust, fear, happiness, sadness, surprise, contempt, and neutral	SAM
[130]	67	Turkey student DB	Private	–	Discrete emotions	Disgust, sadness, happiness, fear, contempt, anger, and surprise	FACS
[243]	2,64,683	SocialMedia	Public	21 mil.	Discrete emotions	Amusement, awe, contentment, excitement, anger, disgust, fear, and sadness	SAM
[305]	–	UNBC-McMaster	Public	48,398	Discrete emotions	Pain and no-pain	FACS

Table C.15
Abbreviations used in the review method.

A
Adaptive VMD (AVMD) Adaptive TQWT (ATQWT) Approximate entropy (APEN) Artificial intelligence (AI) Artificial neural network (ANN) Arousal (A) Attention-based convolutional recurrent neural network (ARCNN) Audio/Video (AV) Autoencoder (AE)
B
Binary class (BC) BiOrthogonal wavelet transform (BOWT) Brain emotional learning (BEL) Broad learning system (BLS)
C
Capsule Net (CapsNet) Continuous wavelet transform (CWT) Convolutional autoencoder (CAE) Convolutional neural network (CNN) Convolutional Block Attention Module (CBAM) Cross validation (CV)
D
Decomposition (DEC) Deep forest (DFR) Deep belief networks (DBN) Deep learning (DL) deep multilayer perceptron (DMLP) Deep neural network (DNN) Differential Emotions Scale (DES) Differential entropy (DE) Directed Acyclic Graph (DAG) Discrete cosine transform (DCT) Discrete Fourier transform (DFT) Discrete wavelet transform (DWT) Dominance (D) Dual filtering (DF) Dual-tree complex wavelet transform (DT-CWT) Dynamic graph neural network (DGNN) Dynamical Graph CNN (DGCNN)
E
Empirical mode decomposition (EMD) Energy effective (EE) Entropy (ENT) Extreme learning machine (ELM)
F
Facial Action Coding System (FACS) Facial landmark coordinates (FLC) Familiarity (FAM) Fast Fourier transform (FFT) Fine KNN (FKNN) Flexible analytic wavelet transform (FAWT) Fold cross validation (FCV) Fourier transform (FT) Fractal dimension (FD) Fractal Firat pattern (FFP) Frequency-domain features (FDF) Fuzzy Hidden Markov Model (FHMM)

(continued on next page)

Table C.15 (*continued*).

G
Generalized low-rank model (GLRM) Generative adversarial network (GAN) Geneva Emotional Music Scale (GEMS) Geometry Guided Pose-Invariant (GGPI) Geometric Mean based Weighted Local Binary Pattern (GM-WLBP) Graph ELM (GELM) Gray Level Co-occurrence Matrix (GLCM) Graph-regularized least square regression with feature importance learning (GFIL)
H
Hamilton Anxiety Rating Scale (HAM-A) Heart rate variability (HRV) High arousal (HA) High valence (HV) Hilbert Huang transform (HHT) Histogram of oriented gradients (HOG)
I
Information potential feature (IPF)
K
K nearest neighbor (KNN)
L
Leave one subject out (LOSO) Least square SVM (LSSVM) Linear features (LF) Linear discriminant analysis (LDA) Linear Predictive correlation coefficient (LPCC) Local binary pattern (LBP) Log Mel-spectrograms (LMSG) Long short term memory (LSTM) Low arousal (LA) Low valence (LV) Lyapunov exponents (LE)
M
Machine learning (ML) Mel-frequency cepstrum coefficients (MFCC) Mel spectrogram (MSG) Modulation spectral (MS) Morphological features (MRF) Multiband feature matrix (MBFM) Multiclass (MC) Multilevel stationary wavelet gradient transform (MSWGT) Multi Task Convolutional Neural Network (MTCNN) Multivariate EMD (MEMD) Multivariate VMD (MVMD)
N
Naïve Bayes (NB) Negative (Neg) Network pattern (NetP) Neutral (Neu) Nonlinear features (NLF)
O
One (1)-dimensional (1D) Optical flow Spatial-Temporal feature (OFSTF)

(continued on next page)

Table C.15 (*continued*).

P
Pearson's Correlation Coefficient (PCC) Philippot questionnaire: emotion state (PQES) Poincare plots (PCP) Positive and Negative Affect Schedule (PANAS) Positive (Pos) Power spectral density (PSD) Prime pattern (PP) Probabilistic neural network (PNN) Prosodic and spectral features (PSF) Prosodic, spectral and cepstral features (PSCF)
Q
Quadratic discriminant analysis (QDA) Quadratic time-frequency distributions (QTFDs)
R
Random forest (RF) Regularized Graph Neural Networks (RGNN) Relevance vector machine (RVM) Residual block (RB)
S
S-transform (S-TF) Scale-invariant feature transform (SIFT) Sample Entropy (SaENT) Self-Assessment Manikin (SAM) Selflearned (SL) Short-time Fourier transform (STFT) Showlace pattern (SLP) Simple Recurrent Units (SRU) Smoothed Pseudo Wigner Ville distribution (SPWVD) Speech-to-image transform (SIT) Spectrogram (SG) Spectral centroids featurs (SCF) State-Trait Anxiety Inventory (STAI) Statistical features (STSF) Support vector machine (SVM)
T
Time-domain features (TDF) Time order representation (TOR) Topographic and holographic feature maps (THFM) Tunable Q wavvelet transform (TQWT) Twine shuffle pattern (TSP)
U
Understandable level (UL)
V
Valence (V) Variational mode decomposition (VMD) Virtual reality (VR)
W
Wavelet decomposition (WDEC) Wavelet energy (WE) Wavelet scattering transform (WST) Wavelet transform (WT)
Z
Zero-crossing rate (ZCR)

References

[1] K. Kamble, J. Sengupta, A comprehensive survey on emotion recognition based on electroencephalograph (EEG) signals, Multimedia Tools Appl. (2023) 1–36.

[2] R.E. Dahl, A.G. Harvey, Sleep in children and adolescents with behavioral and emotional disorders, Sleep Med. Clin. 2 (3) (2007) 501–511, http://dx.doi.org/10.1016/j.jsmc.2007.05.002, Sleep in Children and Adolescents. URL https://www.sciencedirect.com/science/article/pii/S1556407X07000513.

[3] T.E. Feinberg, A. Rifkin, C. Schaffer, E. Walker, Facial discrimination and emotional recognition in schizophrenia and affective disorders, Arch. Gen. Psychiatry 43 (3) (1986) 276–279, http://dx.doi.org/10.1001/archpsyc.1986.01800030094010.

[4] I.B. Mauss, A.S. Troy, M.K. LeBourgeois, Poorer sleep quality is associated with lower emotion-regulation ability in a laboratory paradigm, Cogn. Emot. 27 (3) (2013) 567–576, http://dx.doi.org/10.1080/02699931.2012.727783, PMID: 23025547. arXiv:https://doi.org/10.1080/02699931.2012.727783.

[5] M.N. Dar, M.U. Akram, R. Yuvaraj, S. Gul Khawaja, M. Murugappan, EEG-based emotion charting for Parkinson's disease patients using Convolutional Recurrent Neural Networks and cross dataset learning, Comput. Biol. Med. 144 (2022) 105327, http://dx.doi.org/10.1016/j.compbiomed.2022.105327, URL https://www.sciencedirect.com/science/article/pii/S0010482522001196.

[6] J. Sun, J. Han, Y. Wang, P. Liu, Memristor-based neural network circuit of emotion congruent memory with mental fatigue and emotion inhibition, IEEE Trans. Biomed. Circuits Syst. 15 (3) (2021) 606–616, http://dx.doi.org/10.1109/TBCAS.2021.3090786.

[7] S.S. Jasim, A.K.A. Hassan, Modern drowsiness detection techniques: A review, Int. J. Electr. Comput. Eng. 12 (3) (2022) 2986.

[8] P. Lucey, J.F. Cohn, I. Matthews, S. Lucey, S. Sridharan, J. Howlett, K.M. Prkachin, Automatically detecting pain in video through facial action units, IEEE Trans. Syst. Man Cybern. B 41 (3) (2011) 664–674, http://dx.doi.org/10.1109/TSMCB.2010.2082525.

[9] N. Jamil, N.H.M. Khir, M. Ismail, F.H.A. Razak, Gait-based emotion detection of children with autism spectrum disorders: a preliminary investigation, Procedia Comput. Sci. 76 (2015) 342–348.

[10] S. López-Martín, J. Albert, A. Fernández-Jaén, L. Carretié, Emotional distraction in boys with ADHD: Neural and behavioral correlates, Brain Cogn. 83 (1) (2013) 10–20, http://dx.doi.org/10.1016/j.bandc.2013.06.004, URL https://www.sciencedirect.com/science/article/pii/S0278262613000845.

[11] T. Kircher, V. Arolt, A. Jansen, M. Pyka, I. Reinhardt, T. Kellermann, C. Konrad, U. Lueken, A.T. Gloster, A.L. Gerlach, A. Ströhle, A. Wittmann, B. Pfleiderer, H.-U. Wittchen, B. Straube, Effect of cognitive-behavioral therapy on neural correlates of fear conditioning in panic disorder, Biol. Psychiat. 73 (1) (2013) 93–101, http://dx.doi.org/10.1016/j.biopsych.2012.07.026, Structural and Functional Activity with Stress and Anxiety. URL https://www.sciencedirect.com/science/article/pii/S0006322312006701.

[12] T. Dalgleish, The emotional brain, Nat. Rev. Neurosci. 5 (7) (2004) 583–589.

[13] T.S. Rached, A. Perkusich, Emotion recognition based on brain-computer interface systems, in: R. Fazel-Rezai (Ed.), Brain-Computer Interface Systems, IntechOpen, Rijeka, 2013, http://dx.doi.org/10.5772/56227, Ch. 13.

[14] P. Ekman, An argument for basic emotions, Cogn. Emot. 6 (3–4) (1992) 169–200.

[15] R. Plutchik, H. Kellerman, Theories of Emotion, Vol. 1, Academic Press, 2013.

[16] G.F. Wilson, C.A. Russell, Real-time assessment of mental workload using psychophysiological measures and artificial neural networks, Hum. Factors 45 (4) (2003) 635–644.

[17] A. Mehrabian, Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in temperament, Curr. Psychol. 14 (1996) 261–292.

[18] V. Tran, Positive affect negative affect scale (PANAS), in: Encyclopedia of Behavioral Medicine, Springer, 2020, pp. 1708–1709.

[19] M.M. Bradley, P.J. Lang, Measuring emotion: The self-assessment manikin and the semantic differential, J. Behav. Ther. Exp. Psychiatry 25 (1) (1994) 49–59, http://dx.doi.org/10.1016/0005-7916(94)90063-9, URL https://www.sciencedirect.com/science/article/pii/0005791694900639.

[20] J.P. Pollak, P. Adams, G. Gay, PAM: A photographic affect meter for frequent, in situ measurement of affect, CHI '11, Association for Computing Machinery, New York, NY, USA, 2011, pp. 725–734, http://dx.doi.org/10.1145/1978942.1979047.

[21] S. Kang, C.Y. Park, A. Kim, N. Cha, U. Lee, Understanding emotion changes in mobile experience sampling, CHI '22, Association for Computing Machinery, New York, NY, USA, 2022, http://dx.doi.org/10.1145/3491102.3501944.

[22] L. Shu, J. Xie, M. Yang, Z. Li, Z. Li, D. Liao, X. Xu, X. Yang, A review of emotion recognition using physiological signals, Sensors 18 (7) (2018) 2074.

[23] H. Perry Fordson, X. Xing, K. Guo, X. Xu, Emotion recognition with knowledge graph based on electrodermal activity, Front. Neurosci. 16 (2022) 911767.

[24] F. Larradet, R. Niewiadomski, G. Barresi, D.G. Caldwell, L.S. Mattos, Toward emotion recognition from physiological signals in the wild: approaching the methodological issues in real-life data collection, Front. Psychol. 11 (2020) 1111.

[25] D. Grühn, N. Sharifian, 7 - Lists of emotional stimuli, in: H.L. Meiselman (Ed.), Emotion Measurement, Woodhead Publishing, 2016, pp. 145–164, http://dx.doi.org/10.1016/B978-0-08-100508-8.00007-2, URL https://www.sciencedirect.com/science/article/pii/B9780081005088000072.

[26] G.N. Yannakakis, A. Paiva, Emotion in games, in: Handbook on Affective Computing, Vol. 2014, Oxford University Press, 2014, pp. 459–471.

[27] R. Somarathna, T. Bednarz, G. Mohammadi, Virtual reality for emotion elicitation – a review, IEEE Trans. Affect. Comput. (2022) 1–21, http://dx.doi.org/10.1109/taffc.2022.3181053.

[28] M.A. Hasnul, N.A.A. Aziz, S. Alelyani, M. Mohana, A.A. Aziz, Electrocardiogram-based emotion recognition systems and their applications in healthcare—A review, Sensors 21 (15) (2021) http://dx.doi.org/10.3390/s21155015, URL https://www.mdpi.com/1424-8220/21/15/5015.

[29] P.J. Bota, C. Wang, A.L.N. Fred, H. Plácido Da Silva, A review, current challenges, and future possibilities on emotion recognition using machine learning and physiological signals, IEEE Access 7 (2019) 140990–141020, http://dx.doi.org/10.1109/ACCESS.2019.2944001.

[30] Y.B. Singh, S. Goel, A systematic literature review of speech emotion recognition approaches, Neurocomputing 492 (2022) 245–263, http://dx.doi.org/10.1016/j.neucom.2022.04.028, URL https://www.sciencedirect.com/science/article/pii/S0925231222003964.

[31] K. Kamble, J. Sengupta, A comprehensive survey on emotion recognition based on electroencephalograph (EEG) signals, Multimedia Tools Appl. (2023) 1–36.

[32] J. Zhang, Z. Yin, P. Chen, S. Nichele, Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review, Inf. Fusion 59 (2020) 103–126, http://dx.doi.org/10.1016/j.inffus.2020.01.011, URL https://www.sciencedirect.com/science/article/pii/S1566253519302532.

[33] R.R. Adyapady, B. Annappa, A comprehensive review of facial expression recognition techniques, Multimedia Syst. 29 (1) (2023) 73–103.

[34] S. Ba, X. Hu, Measuring emotions in education using wearable devices: A systematic review, Comput. Educ. 200 (2023) 104797, http://dx.doi.org/10.1016/j.compedu.2023.104797.

[35] D. Moher, A. Liberati, J. Tetzlaff, D.G. Altman, P. Group*, Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement, Ann. Intern. Med. 151 (4) (2009) 264–269.

[36] S.K. Khare, V. Bajaj, G.R. Sinha, Automatic drowsiness detection based on variational non-linear chirp mode decomposition using electroencephalogram signals, in: Modelling and Analysis of Active Biopotential Signals in Healthcare, Volume 1, in: 2053-2563, IOP Publishing, 2020, http://dx.doi.org/10.1088/978-0-7503-3279-8ch5, 5–1 to 5–25.

[37] S.K. Khare, V. Bajaj, A self-learned decomposition and classification model for schizophrenia diagnosis, Comput. Methods Programs Biomed. 211 (2021) 106450, http://dx.doi.org/10.1016/j.cmpb.2021.106450, URL https://www.sciencedirect.com/science/article/pii/S0169260721005241.

[38] S.K. Khare, N.B. Gaikwad, V. Bajaj, VHERS: A novel variational mode decomposition and Hilbert transform-based EEG rhythm separation for automatic ADHD detection, IEEE Trans. Instrum. Meas. 71 (2022) 1–10, http://dx.doi.org/10.1109/TIM.2022.3204076.

[39] S.K. Khare, S. March, P.D. Barua, V.M. Gadre, U.R. Acharya, Application of data fusion for automated detection of children with developmental and mental disorders: A systematic review of the last decade, Inf. Fusion 99 (2023) 101898, http://dx.doi.org/10.1016/j.inffus.2023.101898, URL https://www.sciencedirect.com/science/article/pii/S1566253523002142.

[40] A.H. Krishna, A.B. Sri, K.Y.V.S. Priyanka, S. Taran, V. Bajaj, Emotion classification using EEG signals based on tunable-q wavelet transform, IET Sci. Meas. Technol. 13 (3) (2019) 375–380, http://dx.doi.org/10.1049/iet-smt.2018.5237, arXiv:https://ietresearch.onlinelibrary.wiley.com/doi/pdf/10.1049/iet-smt.2018.5237. URL https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-smt.2018.5237.

[41] K.S. Kamble, J. Sengupta, Ensemble machine learning-based affective computing for emotion recognition using dual-decomposed EEG signals, IEEE Sens. J. 22 (3) (2022) 2496–2507, http://dx.doi.org/10.1109/JSEN.2021.3135953.

[42] P. Pandey, K. Seeja, Subject independent emotion recognition from EEG using VMD and deep learning, J. King Saud Univ. - Comput. Inf. Sci. 34 (5) (2022) 1730–1738, http://dx.doi.org/10.1016/j.jksuci.2019.11.003, URL https://www.sciencedirect.com/science/article/pii/S1319157819309991.

[43] Z. Mohammadi, J. Frounchi, M. Amiri, Wavelet-based emotion recognition system using EEG signal, Neural Comput. Appl. 28 (2017) 1985–1990.

[44] T. Chen, S. Ju, F. Ren, M. Fan, Y. Gu, EEG emotion recognition model based on the LIBSVM classifier, Measurement 164 (2020) 108047, http://dx.doi.org/10.1016/j.measurement.2020.108047, URL https://www.sciencedirect.com/science/article/pii/S0263224120305856.

[45] Y. Zhang, X. Ji, S. Zhang, An approach to EEG-based emotion recognition using combined feature extraction method, Neurosci. Lett. 633 (2016) 152–157, http://dx.doi.org/10.1016/j.neulet.2016.09.037, URL https://www.sciencedirect.com/science/article/pii/S0304394016307200.

[46] S.K. Khare, V. Bajaj, An evolutionary optimized variational mode decomposition for emotion recognition, IEEE Sens. J. 21 (2) (2021) 2035–2042, http://dx.doi.org/10.1109/JSEN.2020.3020915.

[47] S.K. Khare, V. Bajaj, G.R. Sinha, Adaptive tunable Q wavelet transform-based emotion identification, IEEE Trans. Instrum. Meas. 69 (12) (2020) 9609–9617, http://dx.doi.org/10.1109/TIM.2020.3006611.

[48] V. Gupta, M.D. Chopda, R.B. Pachori, Cross-subject emotion recognition using flexible analytic wavelet transform from EEG signals, IEEE Sens. J. 19 (6) (2019) 2266–2274, http://dx.doi.org/10.1109/JSEN.2018.2883497.

[49] C. Wei, L. lan Chen, Z. zhen Song, X. guang Lou, D. dong Li, EEG-based emotion recognition using simple recurrent units network and ensemble learning, Biomed. Signal Process. Control 58 (2020) 101756, http://dx.doi.org/10.1016/j.bspc.2019.101756, URL https://www.sciencedirect.com/science/article/pii/S1746809419303374.

[50] T. Tuncer, S. Dogan, A. Subasi, A new fractal pattern feature generation function based emotion recognition method using EEG, Chaos Solitons Fractals 144 (2021) 110671, http://dx.doi.org/10.1016/j.chaos.2021.110671, URL https://www.sciencedirect.com/science/article/pii/S0960077921000242.

[51] P. V., A. Bhattacharyya, Human emotion recognition based on time–frequency analysis of multivariate EEG signal, Knowl.-Based Syst. 238 (2022) 107867, http://dx.doi.org/10.1016/j.knosys.2021.107867, URL https://www.sciencedirect.com/science/article/pii/S0950705121010455.

[52] N. Zhuang, Y. Zeng, L. Tong, C. Zhang, H. Zhang, B. Yan, Emotion recognition from EEG signals using multidimensional information in EMD domain, BioMed Res. Int. 2017 (2017).

[53] T. Song, W. Zheng, C. Lu, Y. Zong, X. Zhang, Z. Cui, MPED: A multi-modal physiological emotion database for discrete emotion recognition, IEEE Access 7 (2019) 12177–12191, http://dx.doi.org/10.1109/ACCESS.2019.2891579.

[54] A. Dogan, M. Akay, P.D. Barua, M. Baygin, S. Dogan, T. Tuncer, A.H. Dogru, U.R. Acharya, PrimePatNet87: Prime pattern and tunable q-factor wavelet transform techniques for automated accurate EEG emotion recognition, Comput. Biol. Med. 138 (2021) 104867, http://dx.doi.org/10.1016/j.compbiomed.2021.104867, URL https://www.sciencedirect.com/science/article/pii/S0010482521006612.

[55] E. Deniz, N. Sobahi, N. Omar, A. Sengur, U.R. Acharya, Automated robust human emotion classification system using hybrid EEG features with ICBrainDB dataset, Health Inf. Sci. Syst. 10 (1) (2022) 31.

[56] M.R. Islam, M.M. Islam, M.M. Rahman, C. Mondal, S.K. Singha, M. Ahmad, A. Awal, M.S. Islam, M.A. Moni, EEG channel correlation based model for emotion recognition, Comput. Biol. Med. 136 (2021) 104757, http://dx.doi.org/10.1016/j.compbiomed.2021.104757, URL https://www.sciencedirect.com/science/article/pii/S0010482521005515.

[57] F. Wang, S. Wu, W. Zhang, Z. Xu, Y. Zhang, C. Wu, S. Coleman, Emotion recognition with convolutional neural network and EEG-based EFDMs, Neuropsychologia 146 (2020) 107506, http://dx.doi.org/10.1016/j.neuropsychologia.2020.107506, URL https://www.sciencedirect.com/science/article/pii/S0028393220301780.

[58] S.K. Khare, V. Bajaj, Time–frequency representation and convolutional neural network-based emotion recognition, IEEE Trans. Neural Netw. Learn. Syst. 32 (7) (2021) 2901–2909, http://dx.doi.org/10.1109/TNNLS.2020.3008938.

[59] P. Li, H. Liu, Y. Si, C. Li, F. Li, X. Zhu, X. Huang, Y. Zeng, D. Yao, Y. Zhang, P. Xu, EEG based emotion recognition by combining functional connectivity network and local activations, IEEE Trans. Biomed. Eng. 66 (10) (2019) 2869–2881, http://dx.doi.org/10.1109/TBME.2019.2897651.

[60] X. Du, C. Ma, G. Zhang, J. Li, Y.-K. Lai, G. Zhao, X. Deng, Y.-J. Liu, H. Wang, An efficient LSTM network for emotion recognition from multichannel EEG signals, IEEE Trans. Affect. Comput. 13 (3) (2022) 1528–1540, http://dx.doi.org/10.1109/TAFFC.2020.3013711.

[61] S. Khare, A. Nishad, A. Upadhyay, V. Bajaj, Classification of emotions from EEG signals using time-order representation based on the S-transform and convolutional neural network, Electron. Lett. 56 (25) (2020) 1359–1361, http://dx.doi.org/10.1049/el.2020.2380, arXiv:https://ietresearch.onlinelibrary.wiley.com/doi/pdf/10.1049/el.2020.2380. URL https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/el.2020.2380.

[62] R. Alazrai, R. Homoud, H. Alwanni, M.I. Daoud, EEG-based emotion recognition using quadratic time-frequency distribution, Sensors 18 (8) (2018) http://dx.doi.org/10.3390/s18082739, URL https://www.mdpi.com/1424-8220/18/8/2739.

[63] A. Topic, M. Russo, Emotion recognition based on EEG feature maps through deep learning network, Eng. Sci. Technol. Int. J. 24 (6) (2021) 1442–1454, http://dx.doi.org/10.1016/j.jestch.2021.03.012, URL https://www.sciencedirect.com/science/article/pii/S2215098621000768.

[64] S. Hwang, K. Hong, G. Son, H. Byun, Learning CNN features from DE features for EEG-based emotion recognition, Pattern Anal. Appl. 23 (2020) 1323–1335.

[65] A. Sepúlveda, F. Castillo, C. Palma, M. Rodriguez-Fernandez, Emotion recognition from ECG signals using wavelet scattering and machine learning, Appl. Sci. 11 (11) (2021) http://dx.doi.org/10.3390/app11114945, URL https://www.mdpi.com/2076-3417/11/11/4945.

[66] K.N. Minhad, S.H.M. Ali, M.B.I. Reaz, Happy-anger emotions classifications from electrocardiogram signal for automobile driving safety and awareness, J. Transp. Health 7 (2017) 75–89, http://dx.doi.org/10.1016/j.jth.2017.11.001, Road Danger Reduction. URL https://www.sciencedirect.com/science/article/pii/S2214140516303693.

[67] R. Subramanian, J. Wache, M.K. Abadi, R.L. Vieriu, S. Winkler, N. Sebe, ASCERTAIN: Emotion and personality recognition using commercial sensors, IEEE Trans. Affect. Comput. 9 (2) (2018) 147–160, http://dx.doi.org/10.1109/TAFFC.2016.2625250.

[68] K. NISA'MINHAD, S.H.M. Ali, M.B.I. Reaz, A design framework for human emotion recognition using electrocardiogram and skin conductance response signals, J. Eng. Sci. Technol. 12 (11) (2017) 3102–3119.

[69] J. Selvaraj, M. Murugappan, K. Wan, S. Yaacob, Classification of emotional states from electrocardiogram signals: a non-linear approach based on hurst, Biomed. Eng. Online 12 (1) (2013) 1–18.

[70] S.-T. Pan, W.-C. Li, Fuzzy-HMM modeling for emotion detection using electrocardiogram signals, Asian J. Control 22 (6) (2020) 2206–2216, http://dx.doi.org/10.1002/asjc.2375, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/asjc.2375. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/asjc.2375.
[71] T. Chen, H. Yin, X. Yuan, Y. Gu, F. Ren, X. Sun, Emotion recognition based on fusion of long short-term memory networks and SVMs, Digit. Signal Process. 117 (2021) 103153, http://dx.doi.org/10.1016/j.dsp.2021.103153, URL https://www.sciencedirect.com/science/article/pii/S1051200421001925.
[72] M. Nardelli, G. Valenza, A. Greco, A. Lanata, E.P. Scilingo, Recognizing emotions induced by affective sounds through heart rate variability, IEEE Trans. Affect. Comput. 6 (4) (2015) 385–394, http://dx.doi.org/10.1109/TAFFC.2015.2432810.
[73] S. Nita, S. Bitam, M. Heidet, A. Mellouk, A new data augmentation convolutional neural network for human emotion recognition based on ECG signals, Biomed. Signal Process. Control 75 (2022) 103580, http://dx.doi.org/10.1016/j.bspc.2022.103580, URL https://www.sciencedirect.com/science/article/pii/S1746809422001021.
[74] F.E. Oğuz, A. Alkan, T. Schöler, Emotion detection from ECG signals with different learning algorithms and automated feature engineering, Signal Image Video Process. (2023) 1–9.
[75] Y.-L. Hsu, J.-S. Wang, W.-C. Chiang, C.-H. Hung, Automatic ECG-based emotion recognition in music listening, IEEE Trans. Affect. Comput. 11 (1) (2020) 85–99, http://dx.doi.org/10.1109/TAFFC.2017.2781732.
[76] J. S, M. Murugappan, K. Wan, S. Yaacob, Electrocardiogram-based emotion recognition system using empirical mode decomposition and discrete Fourier transform, Expert Syst. 31 (2) (2014) 110–120, http://dx.doi.org/10.1111/exsy.12014.
[77] An accurate emotion recognition system using ECG and GSR signals and matching pursuit method.
[78] T. Dissanayake, Y. Rajapaksha, R. Ragel, I. Nawinne, An ensemble learning approach for electrocardiogram sensor based human emotion recognition, Sensors 19 (20) (2019) http://dx.doi.org/10.3390/s19204495, URL https://www.mdpi.com/1424-8220/19/20/4495.
[79] D.S. Hammad, H. Monkaresi, ECG-based emotion detection via parallel-extraction of temporal and spatial features using convolutional neural network, Trait. Signal 39 (1) (2022).
[80] T. Fan, S. Qiu, Z. Wang, H. Zhao, J. Jiang, Y. Wang, J. Xu, T. Sun, N. Jiang, A new deep convolutional neural network incorporating attentional mechanisms for ECG emotion recognition, Comput. Biol. Med. 159 (2023) 106938, http://dx.doi.org/10.1016/j.compbiomed.2023.106938, URL https://www.sciencedirect.com/science/article/pii/S0010482523004031.
[81] A.N. Khan, A.A. Ihalage, Y. Ma, B. Liu, Y. Liu, Y. Hao, Deep learning framework for subject-independent emotion detection using wireless signals, PLOS ONE 16 (2) (2021) 1–16, http://dx.doi.org/10.1371/journal.pone.0242946.
[82] M.N. Dar, M.U. Akram, S.G. Khawaja, A.N. Pujari, CNN and LSTM-based emotion charting using physiological signals, Sensors 20 (16) (2020) http://dx.doi.org/10.3390/s20164551, URL https://www.mdpi.com/1424-8220/20/16/4551.
[83] P. Sarkar, A. Etemad, Self-supervised ECG representation learning for emotion recognition, IEEE Trans. Affect. Comput. 13 (3) (2022) 1541–1554, http://dx.doi.org/10.1109/TAFFC.2020.3014842.
[84] A. Raheel, M. Majid, M. Alnowami, S.M. Anwar, Physiological sensors based emotion recognition while experiencing tactile enhanced multimedia, Sensors 20 (14) (2020) http://dx.doi.org/10.3390/s20144037, URL https://www.mdpi.com/1424-8220/20/14/4037.
[85] D. Ayata, Y. Yaslan, M. Kamasak, Emotion recognition via galvanic skin response: Comparison of machine learning algorithms and feature extraction methods, Istanb. Univ. - J. Electr. Electron. Eng. 17 (2017) ISSN: 1303–0914.
[86] Application of fractional Fourier transform in feature extraction from ELECTROCARDIOGRAM and GALVANIC SKIN RESPONSE for emotion recognition.
[87] A. Goshvarpour, A. Goshvarpour, The potential of photoplethysmogram and galvanic skin response in emotion recognition using nonlinear features, Phys. Eng. Sci. Med. 43 (1) (2020) 119–134.
[88] C. Li, C. Xu, Z. Feng, Analysis of physiological for emotion recognition with the IRS model, Neurocomputing 178 (2016) 103–111, http://dx.doi.org/10.1016/j.neucom.2015.07.112, Smart Computing for Large Scale Visual Data Sensing and Processing. URL https://www.sciencedirect.com/science/article/pii/S0925231215016045.
[89] A Shrewd Artificial Neural Network-Based Hybrid Model for Pervasive Stress Detection of Students Using Galvanic Skin Response and Electrocardiogram Signals.
[90] A. Goshvarpour, A. Abbasi, A. Goshvarpour, S. Daneshvar, Discrimination between different emotional states based on the chaotic behavior of galvanic skin responses, Signal Image Video Process. 11 (2017) 1347–1355.
[91] J. Domínguez-Jiménez, K. Campo-Landines, J. Martínez-Santos, E. Delahoz, S. Contreras-Ortiz, A machine learning model for emotion recognition from physiological signals, Biomed. Signal Process. Control 55 (2020) 101646, http://dx.doi.org/10.1016/j.bspc.2019.101646, URL https://www.sciencedirect.com/science/article/pii/S1746809419302277.
[92] Fusion framework for emotional electrocardiogram and galvanic skin response recognition: Applying wavelet transform.
[93] A. Goshvarpour, A. Abbasi, A. Goshvarpour, S. Daneshvar, A novel signal-based fusion approach for accurate music emotion recognition, Biomed. Eng.: Appl. Basis Commun. 28 (06) (2016) 1650040, http://dx.doi.org/10.4015/S101623721650040X, arXiv:https://doi.org/10.4015/S101623721650040X.
[94] X. Sun, T. Hong, C. Li, F. Ren, Hybrid spatiotemporal models for sentiment classification via galvanic skin response, Neurocomputing 358 (2019) 385–400, http://dx.doi.org/10.1016/j.neucom.2019.05.061, URL https://www.sciencedirect.com/science/article/pii/S0925231219307672.
[95] D.-H. Kang, D.-H. Kim, 1D convolutional autoencoder-based PPG and GSR signals for real-time emotion classification, IEEE Access.
[96] Y. Li, J. Deng, Q. Wu, Y. Wang, Eye-tracking signals based affective classification employing deep gradient convolutional neural networks, 2021.
[97] V. Skaramagkas, E. Ktistakis, D. Manousos, E. Kazantzaki, N.S. Tachos, E. Tripoliti, D.I. Fotiadis, M. Tsiknakis, eSEE-d: Emotional state estimation based on eye-tracking dataset, Brain Sci. 13 (4) (2023) 589.
[98] N. Baharom, N. Jayabalan, M. Amin, S. Wibirama, Positive emotion recognition through eye tracking technology, J. Adv. Manuf. Technol. (JAMT) 13 (2(1)) (1 1). URL https://jamt.utem.edu.my/jamt/article/view/5683.
[99] D. Bethge, L. Chuang, T. Grosse-Puppendahl, Analyzing transferability of happiness detection via gaze tracking in multimedia applications, in: ACM Symposium on Eye Tracking Research and Applications, in: ETRA '20 Adjunct, Association for Computing Machinery, New York, NY, USA, 2020, http://dx.doi.org/10.1145/3379157.3391655.
[100] Y. Stylianou, Voice transformation: A survey, in: 2009 IEEE International Conference on Acoustics, Speech and Signal Processing, 2009, pp. 3585–3588, http://dx.doi.org/10.1109/ICASSP.2009.4960401.
[101] A. Christy, S. Vaithyasubramanian, J. A., M. Praveena, Multimodal speech emotion recognition and classification using convolutional neural network techniques, Int. J. Speech Technol. 23 (2020) 381–388, http://dx.doi.org/10.1007/s10772-020-09713-y.
[102] M. Jain, S. Narayan, P. Balaji, B.K. P, A. Bhowmick, K. R, R.K. Muthu, Speech emotion recognition using support vector machine, 2020, arXiv:2002.07590.
[103] A. Koduru, H. Valiveti, A. Budati, Feature extraction algorithms to improve the speech emotion recognition rate, Int. J. Speech Technol. 23 (2020) 45–55, http://dx.doi.org/10.1007/s10772-020-09672-4.
[104] M. Ren, W. Nie, A. Liu, Y. Su, Multi-modal Correlated Network for emotion recognition in speech, Vis. Inform. 3 (3) (2019) 150–155, http://dx.doi.org/10.1016/j.visinf.2019.10.003, URL https://www.sciencedirect.com/science/article/pii/S2468502X19300488.
[105] Z. Yang, Y. Huang, Algorithm for speech emotion recognition classification based on Mel-frequency Cepstral coefficients and broad learning system, Evol. Intell. 15 (2021) 2485–2494, http://dx.doi.org/10.1007/s12065-020-00532-3.
[106] K. Wang, N. An, B.N. Li, Y. Zhang, L. Li, Speech emotion recognition using Fourier parameters, IEEE Trans. Affect. Comput. 6 (1) (2015) 69–75, http://dx.doi.org/10.1109/TAFFC.2015.2392101.
[107] S. Tripathi, A. Kumar, A. Ramesh, C. Singh, P. Yenigalla, Deep learning based emotion recognition system using speech features and transcriptions, 2019, arXiv:1906.05681.
[108] A. Bhavan, P. Chauhan, Hitkul, R.R. Shah, Bagged support vector machines for emotion recognition from speech, Knowl.-Based Syst. 184 (2019) 104886, http://dx.doi.org/10.1016/j.knosys.2019.104886, URL https://www.sciencedirect.com/science/article/pii/S0950705119303533.
[109] Z.-T. Liu, Q. Xie, M. Wu, W.-H. Cao, Y. Mei, J.-W. Mao, Speech emotion recognition based on an improved brain emotion learning model, Neurocomputing 309 (2018) 145–156, http://dx.doi.org/10.1016/j.neucom.2018.05.005, URL https://www.sciencedirect.com/science/article/pii/S0925231218305344.
[110] H. Xu, H. Zhang, K. Han, Y. Wang, Y. Peng, X. Li, Learning alignment for multimodal emotion recognition from speech, 2020, arXiv:1909.05645.
[111] M. Farooq, F. Hussain, N.K. Baloch, F.R. Raja, H. Yu, Y.B. Zikria, Impact of feature selection algorithm on speech emotion recognition using deep convolutional neural network, Sensors 20 (21) (2020) http://dx.doi.org/10.3390/s20216008, URL https://www.mdpi.com/1424-8220/20/21/6008.
[112] Mustaqeem, S. Kwon, Optimal feature selection based speech emotion recognition using two-stream deep convolutional neural network, Int. J. Intell. Syst. 36 (9) (2021) 5116–5135, http://dx.doi.org/10.1002/int.22505, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/int.22505. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/int.22505.
[113] D. Issa, M. Fatih Demirci, A. Yazici, Speech emotion recognition with deep convolutional neural networks, Biomed. Signal Process. Control 59 (2020) 101894, http://dx.doi.org/10.1016/j.bspc.2020.101894, URL https://www.sciencedirect.com/science/article/pii/S1746809420300501.
[114] Mustaqeem, S. Kwon, A CNN-assisted enhanced audio signal processing for speech emotion recognition, Sensors 20 (1) (2020) http://dx.doi.org/10.3390/s20010183, URL https://www.mdpi.com/1424-8220/20/1/183.
[115] A. Bakhshi, A. Harimi, S. Chalup, CyTex: Transforming speech to textured images for speech emotion recognition, Speech Commun. 139 (2022) 62–75, http://dx.doi.org/10.1016/j.specom.2022.02.007, URL https://www.sciencedirect.com/science/article/pii/S0167639322000310.

[116] A. Badshah, N. Rahim, N. Ullah, J. Ahmad, K. Muhammad, M. Lee, S. Kwon, S. Baik, Deep features-based speech emotion recognition for smart affective services, Multimedia Tools Appl. 78 (2019) 5571–5589, http://dx.doi.org/10.1007/s11042-017-5292-7.

[117] S. Zhang, S. Zhang, T. Huang, W. Gao, Speech emotion recognition using deep convolutional neural network and discriminant temporal pyramid matching, IEEE Trans. Multimed. 20 (6) (2018) 1576–1590, http://dx.doi.org/10.1109/TMM.2017.2766843.

[118] Y. Xie, R. Liang, Z. Liang, C. Huang, C. Zou, B. Schuller, Speech emotion classification using attention-based LSTM, IEEE/ACM Trans. Audio Speech Lang. Process. 27 (11) (2019) 1675–1685, http://dx.doi.org/10.1109/TASLP.2019.2925934.

[119] Mustaqeem, M. Sajjad, S. Kwon, Clustering-based speech emotion recognition by incorporating learned features and deep BiLSTM, IEEE Access 8 (2020) 79861–79875, http://dx.doi.org/10.1109/ACCESS.2020.2990405.

[120] S. Kanwal, S. Asghar, Speech emotion recognition using clustering based GA-optimized feature set, IEEE Access 9 (2021) 125830–125842, http://dx.doi.org/10.1109/ACCESS.2021.3111659.

[121] Z. Xiao, E. Dellandréa, W. Dou, L. Chen, Multi-stage classification of emotional speech motivated by a dimensional emotion model, Multimedia Tools Appl. 46 (2010) 119–145, http://dx.doi.org/10.1007/s11042-009-0319-3.

[122] H.A. Shehu, W.N. Browne, H. Eisenbarth, An anti-attack method for emotion categorization from images, Appl. Soft Comput. 128 (2022) 109456, http://dx.doi.org/10.1016/j.asoc.2022.109456, URL https://www.sciencedirect.com/science/article/pii/S1568494622005695.

[123] S. Kuruvayil, S. Palaniswamy, Emotion recognition from facial images with simultaneous occlusion, pose and illumination variations using meta-learning, J. King Saud Univ. - Comput. Inf. Sci. 34 (9) (2022) 7271–7282, http://dx.doi.org/10.1016/j.jksuci.2021.06.012, URL https://www.sciencedirect.com/science/article/pii/S1319157821001452.

[124] I. Haider, H.-J. Yang, G.-S. Lee, S.-H. Kim, Robust human face emotion classification using triplet-loss-based deep CNN features and SVM, Sensors 23 (10) (2023) http://dx.doi.org/10.3390/s23104770, URL https://www.mdpi.com/1424-8220/23/10/4770.

[125] D. Sen, S. Datta, R. Balasubramanian, Facial emotion classification using concatenated geometric and textural features, Multimedia Tools Appl. 78 (2019) 10287–10323, http://dx.doi.org/10.1007/s11042-018-6537-9.

[126] J. Deng, G. Pang, Z. Zhang, Z. Pang, H. Yang, G. Yang, cGAN based facial expression recognition for human-robot interaction, IEEE Access 7 (2019) 9848–9859, http://dx.doi.org/10.1109/ACCESS.2019.2891668.

[127] A.K. Hassan, S.N. Mohammed, A novel facial emotion recognition scheme based on graph mining, Def. Technol. 16 (5) (2020) 1062–1072, http://dx.doi.org/10.1016/j.dt.2019.12.006, URL https://www.sciencedirect.com/science/article/pii/S2214914719307627.

[128] J.-H. Kim, B.-G. Kim, P.P. Roy, D.-M. Jeong, Efficient facial expression recognition algorithm based on hierarchical deep neural network structure, IEEE Access 7 (2019) 41273–41285, http://dx.doi.org/10.1109/ACCESS.2019.2907327.

[129] J. Li, K. Jin, D. Zhou, N. Kubota, Z. Ju, Attention mechanism-based CNN for facial expression recognition, Neurocomputing 411 (2020) 340–350, http://dx.doi.org/10.1016/j.neucom.2020.06.014, URL https://www.sciencedirect.com/science/article/pii/S0925231220309838.

[130] G. Tonguç, B. Ozaydın Ozkara, Automatic recognition of student emotions from facial expressions during a lecture, Comput. Educ. 148 (2020) 103797, http://dx.doi.org/10.1016/j.compedu.2019.103797, URL https://www.sciencedirect.com/science/article/pii/S0360131519303471.

[131] S.L. Happy, A. Routray, Automatic facial expression recognition using features of salient facial patches, IEEE Trans. Affect. Comput. 6 (1) (2015) 1–12, http://dx.doi.org/10.1109/TAFFC.2014.2386334.

[132] P. Rodriguez, G. Cucurull, J. Gonzàlez, J.M. Gonfaus, K. Nasrollahi, T.B. Moeslund, F.X. Roca, Deep pain: Exploiting long short-term memory networks for facial expression classification, IEEE Trans. Cybern. 52 (5) (2022) 3314–3324, http://dx.doi.org/10.1109/TCYB.2017.2662199.

[133] S. Minaee, M. Minaei, A. Abdolrashidi, Deep-emotion: Facial expression recognition using attentional convolutional network, Sensors 21 (9) (2021) http://dx.doi.org/10.3390/s21093046, URL https://www.mdpi.com/1424-8220/21/9/3046.

[134] W. Xiaohua, P. Muzi, P. Lijuan, H. Min, J. Chunhua, R. Fuji, Two-level attention with two-stage multi-task learning for facial emotion recognition, J. Vis. Commun. Image Represent. 62 (2019) 217–225, http://dx.doi.org/10.1016/j.jvcir.2019.05.009, URL https://www.sciencedirect.com/science/article/pii/S1047320319301646.

[135] T. Rao, M. Xu, D. Xu, Learning multi-level deep representations for image emotion classification, Neural Process. Lett. 51 (2016) 2043–2061.

[136] N. Sun, Q. Li, R. Huan, J. Liu, G. Han, Deep spatial-temporal feature fusion for facial expression recognition in static images, Pattern Recognit. Lett. 119 (2019) 49–61, http://dx.doi.org/10.1016/j.patrec.2017.10.022, Deep Learning for Pattern Recognition. URL https://www.sciencedirect.com/science/article/pii/S0167865517303902.

[137] M.A.H. Akhand, S. Roy, N. Siddique, M.A.S. Kamal, T. Shimamura, Facial emotion recognition using transfer learning in the deep CNN, Electronics 10 (9) (2021) http://dx.doi.org/10.3390/electronics10091036, URL https://www.mdpi.com/2079-9292/10/9/1036.

[138] A. Khattak, M.Z. Asghar, M. Ali, U. Batool, An efficient deep learning technique for facial emotion recognition, Multimedia Tools Appl. 81 (2) (2022) 1649–1683, http://dx.doi.org/10.1007/s11042-021-11298-w.

[139] M. Maithri, U. Raghavendra, A. Gudigar, J. Samanth, P.D. Barua, M. Murugappan, Y. Chakole, U.R. Acharya, Automated emotion recognition: Current trends and future perspectives, Comput. Methods Programs Biomed. 215 (2022) 106646, http://dx.doi.org/10.1016/j.cmpb.2022.106646, URL https://www.sciencedirect.com/science/article/pii/S0169260722000311.

[140] U. Raghavendra, A. Gudigar, Y. Chakole, P. Kasula, D.P. Subha, N.A. Kadri, E.J. Ciaccio, U.R. Acharya, Automated detection and screening of depression using continuous wavelet transform with electroencephalogram signals, Expert Syst. 40 (4) (2023) e12803, http://dx.doi.org/10.1111/exsy.12803, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/exsy.12803. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/exsy.12803.

[141] M.N. Dar, M.U. Akram, R. Yuvaraj, S. Gul Khawaja, M. Murugappan, EEG-based emotion charting for Parkinson's disease patients using Convolutional Recurrent Neural Networks and cross dataset learning, Comput. Biol. Med. 144 (2022) 105327, http://dx.doi.org/10.1016/j.compbiomed.2022.105327, URL https://www.sciencedirect.com/science/article/pii/S0010482522001196.

[142] M. Murugappan, W. Alshuaib, A.K. Bourisly, S.K. Khare, S. Sruthi, V. Bajaj, Tunable Q wavelet transform based emotion classification in Parkinson's disease using Electroencephalography, PLOS ONE 15 (11) (2020) 1–17, http://dx.doi.org/10.1371/journal.pone.0242014.

[143] S. Righi, G. Gronchi, S. Ramat, G. Gavazzi, F. Cecchi, M.P. Viggiano, Automatic and controlled attentional orienting toward emotional faces in patients with Parkinson's disease, Cogn. Affect. Behav. Neurosci. 23 (2) (2023) 371–382.

[144] J. Skibińska, R. Burget, Parkinson's disease detection based on changes of emotions during speech, in: 2020 12th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT), 2020, pp. 124–130, http://dx.doi.org/10.1109/ICUMT51630.2020.9222446.

[145] W.-L. Chu, M.-W. Huang, B.-L. Jian, K.-S. Cheng, Analysis of EEG entropy during visual evocation of emotion in schizophrenia, Ann. Gen. Psychiatry 16 (2017) 1–9.

[146] D.I. Leitman, P. Laukka, P.N. Juslin, E. Saccente, P. Butler, D.C. Javitt, Getting the cue: Sensory contributions to auditory emotion recognition impairments in schizophrenia, Schizophr. Bull. 36 (3) (2008) 545–556, http://dx.doi.org/10.1093/schbul/sbn115, arXiv:https://academic.oup.com/schizophreniabulletin/article-pdf/36/3/545/5311926/sbn115.pdf.

[147] M.K. Mandal, U. Habel, R.C. Gur, Facial expression-based indicators of schizophrenia: Evidence from recent research, Schizophr. Res. 252 (2023) 335–344, http://dx.doi.org/10.1016/j.schres.2023.01.016, URL https://www.sciencedirect.com/science/article/pii/S0920996423000282.

[148] N. Liu, Z. Yuan, Y. Chen, C. Liu, L. Wang, Learning implicit sentiments in Alzheimer's disease recognition with contextual attention features, Front. Aging Neurosci. 15 (2023) 1122799.

[149] W. Maturana, I. Lobo, J. Landeira-Fernandez, D.C. Mograbi, Nondeclarative associative learning in Alzheimer's disease: An overview of eyeblink, fear, and other emotion-based conditioning, Physiol. Behav. 268 (2023) 114250, http://dx.doi.org/10.1016/j.physbeh.2023.114250, URL https://www.sciencedirect.com/science/article/pii/S0031938423001750.

[150] I. Ferrer-Cairols, L. Ferré-González, G. García-Lluch, C. Peña-Bautista, L. Álvarez-Sánchez, M. Baquero, C. Cháfer-Pericás, Emotion recognition and baseline cortisol levels relationship in early Alzheimer disease, Biol. Psychol. 177 (2023) 108511, http://dx.doi.org/10.1016/j.biopsycho.2023.108511, URL https://www.sciencedirect.com/science/article/pii/S0301051123000285.

[151] M. Brandt, F. de Oliveira Silva, J.P.S. Neto, M.A.T. Baptista, T. Belfort, I.B. Lacerda, M.C.N. Dourado, Facial expression recognition of emotional situations in mild and moderate Alzheimer's disease, J. Geriatr. Psychiatry Neurol. 0 (0) (0) 08919887231175432. PMID: 37160761. http://dx.doi.org/10.1177/08919887231175432.

[152] S. Gupta, A. Singh, J. Ranjan, Multimodal, multiview and multitasking depression detection framework endorsed with auxiliary sentiment polarity and emotion detection, Int. J. Syst. Assur. Eng. Manag. (2023) 1–16.

[153] M. Tadalagi, A.M. Joshi, AutoDep: automatic depression detection using facial expressions based on linear binary pattern descriptor, Med. Biol. Eng. Comput. 59 (6) (2021) 1339–1354.

[154] H. Chang, Y. Zong, W. Zheng, C. Tang, J. Zhu, X. Li, Depression assessment method: an EEG emotion recognition framework based on spatiotemporal neural network, Front. Psychiatry 12 (2022) 837149.

[155] Ü. Aydin, R. Cañigueral, C. Tye, G. McLoughlin, Face processing in young adults with autism and ADHD: An event related potentials study, Front. Psychiatry 14 (2023) 1080681.

[156] L. Sacco, L. Morellini, C. Cerami, The diagnosis and the therapy of social cognition deficits in adults affected by ADHD and MCI, Front. Neurol. 14 (2023) 1162510.

[157] E. McKay, K. Cornish, H. Kirk, Impairments in emotion recognition and positive emotion regulation predict social difficulties in adolescent with ADHD, Clin. Child Psychol. Psychiatry 28 (3) (2023) 895–908, http://dx.doi.org/10.1177/13591045221141770, PMID: 36440882.

[158] S. Le Sourn-Bissaoui, M. Aguert, P. Girard, C. Chevreuil, V. Laval, Emotional speech comprehension in children and adolescents with autism spectrum disorders, J. Commun. Disord. 46 (4) (2013) 309–320, http://dx.doi.org/10.1016/j.jcomdis.2013.03.002, URL https://www.sciencedirect.com/science/article/pii/S0021992413000105.

[159] R. Matin, D. Valles, A speech emotion recognition solution-based on support vector machine for children with autism spectrum disorder to help identify human emotions, in: 2020 Intermountain Engineering, Technology and Computing (IETC), 2020, pp. 1–6, http://dx.doi.org/10.1109/IETC47856.2020.9249147.

[160] M. Derbali, M. Jarrah, P. Randhawa, Autism spectrum disorder detection: Video games based facial expression diagnosis using deep learning, Int. J. Adv. Comput. Sci. Appl. 14 (1) (2023).

[161] N.F. Harun, N. Hamzah, N. Zaini, M.M. Sani, H. Norhazman, I.M. Yassin, EEG classification analysis for diagnosing autism spectrum disorder based on emotions, J. Telecommun. Electron. Comput. Eng. (JTEC) 10 (1–2) (2018) 87–93.

[162] S. Pick, J.D. Mellers, L.H. Goldstein, Explicit facial emotion processing in patients with dissociative seizures, Psychosom. Med. 78 (7) (2016) 874–885.

[163] J. Amlerova, A.E. Cavanna, O. Bradac, A. Javurkova, J. Raudenska, P. Marusic, Emotion recognition and social cognition in temporal lobe epilepsy and the effect of epilepsy surgery, Epilepsy Behav. 36 (2014) 86–89, http://dx.doi.org/10.1016/j.yebeh.2014.05.001, URL https://www.sciencedirect.com/science/article/pii/S1525505014001619.

[164] L.W. Carawan, B.A. Nalavany, C. Jenkins, Emotional experience with dyslexia and self-esteem: the protective role of perceived family support in late adulthood, Aging Ment. Health 20 (3) (2016) 284–294, http://dx.doi.org/10.1080/13607863.2015.1008984, PMID: 25660279. arXiv:https://doi.org/10.1080/13607863.2015.1008984.

[165] E. Anyanwu, A. Campbell, Childhood emotional experiences leading to biopsychosocially-induced dyslexia and low academic performance in adolescence, Int. J. Adolesc. Med. Health 13 (3) (2001) 191–204, http://dx.doi.org/10.1515/IJAMH.2001.13.3.191, [cited 2023-08-03].

[166] M. Doikou-Avlidou, The educational, social and emotional experiences of students with dyslexia: The perspective of postsecondary education students, Int. J. Spec. Educ. 30 (1) (2015) 132–145.

[167] P.M. Cole, J. Luby, M.W. Sullivan, Emotions and the development of childhood depression: Bridging the gap, Child Dev. Perspect. 2 (3) (2008) 141–148, http://dx.doi.org/10.1111/j.1750-8606.2008.00056.x, arXiv:https://srcd.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1750-8606.2008.00056.x. URL https://srcd.onlinelibrary.wiley.com/doi/abs/10.1111/j.1750-8606.2008.00056.x.

[168] S. Siener, K.A. Kerns, Emotion regulation and depressive symptoms in preadolescence, Child Psychiatry Hum. Dev. 43 (2012) 414–430.

[169] C. Suveg, J. Zeman, Emotion regulation in children with anxiety disorders, J. Clin. Child Adolesc. Psychol. 33 (4) (2004) 750–759, http://dx.doi.org/10.1207/s15374424jccp3304_10, PMID: 15498742.

[170] D.K. Hannesdottir, T.H. Ollendick, The role of emotion regulation in the treatment of child anxiety disorders, Clin. Child Fam. Psychol. Rev. 10 (2007) 275–293.

[171] F.M. Talaat, Real-time facial emotion recognition system among children with autism based on deep learning and IoT, Neural Comput. Appl. 35 (17) (2023) 12717–12728.

[172] L. Berkovits, A. Eisenhower, J. Blacher, Emotion regulation in young children with autism spectrum disorders, J. Autism Dev. Disord. 47 (2017) 68–79.

[173] C. Ryan, C.N. Charragáin, Teaching emotion recognition skills to children with autism, J. Autism Dev. Disord. 40 (12) (2010) 1505–1511.

[174] V. Blanes-Vidal, J. Bælum, E.S. Nadimi, P. Løfstrøm, L.P. Christensen, Chronic exposure to odorous chemicals in residential areas and effects on human psychosocial health: Dose–response relationships, Sci. Total Environ. 490 (2014) 545–554, http://dx.doi.org/10.1016/j.scitotenv.2014.05.041, URL https://www.sciencedirect.com/science/article/pii/S0048969714007189.

[175] M.L. Cantuaria, J. Brandt, V. Blanes-Vidal, Exposure to multiple environmental stressors, emotional and physical well-being, and self-rated health: An analysis of relationships using latent variable structural equation modelling, Environ. Res. 227 (2023) 115770, http://dx.doi.org/10.1016/j.envres.2023.115770, URL https://www.sciencedirect.com/science/article/pii/S0013935123005625.

[176] P. Weichbroth, W. Sroka, A note on the affective computing systems and machines: A classification and appraisal, Procedia Comput. Sci. 207 (C) (2022) 3798–3807, http://dx.doi.org/10.1016/j.procs.2022.09.441.

[177] D. Caruelle, P. Shams, A. Gustafsson, L. Lervik-Olsen, Affective computing in marketing: practical implications and research opportunities afforded by emotionally intelligent machines, Mark. Lett. 33 (1) (2022) 163–169.

[178] L. Cen, F. Wu, Z.L. Yu, F. Hu, Chapter 2 - A real-time speech emotion recognition system and its application in online learning, in: S.Y. Tettegah, M. Gartmeier (Eds.), Emotions, Technology, Design, and Learning, in: Emotions and Technology, Academic Press, San Diego, 2016, pp. 27–46, http://dx.doi.org/10.1016/B978-0-12-801856-9.00002-5, URL https://www.sciencedirect.com/science/article/pii/B9780128018569000025.

[179] M. Zembylas, M. Theodorou, A. Pavlakis, The role of emotions in the experience of online learning: Challenges and opportunities, Educ. Media Int. 45 (2) (2008) 107–117.

[180] O.S. Lih, V. Jahmunah, E.E. Palmer, P.D. Barua, S. Dogan, T. Tuncer, S. García, F. Molinari, U.R. Acharya, EpilepsyNet: Novel automated detection of epilepsy using transformer model with EEG signals from 121 patient population, Comput. Biol. Med. 164 (2023) 107312, http://dx.doi.org/10.1016/j.compbiomed.2023.107312, URL https://www.sciencedirect.com/science/article/pii/S0010482523007771.

[181] F. Panahi, S. Rashidi, A. Sheikhani, Application of fractional Fourier transform in feature extraction from ELECTROCARDIOGRAM and GALVANIC SKIN RESPONSE for emotion recognition, Biomed. Signal Process. Control 69 (2021) 102863, http://dx.doi.org/10.1016/j.bspc.2021.102863, URL https://www.sciencedirect.com/science/article/pii/S1746809421004602.

[182] H.W. Loh, C.P. Ooi, S.L. Oh, P.D. Barua, Y.R. Tan, F. Molinari, S. March, U.R. Acharya, D.S.S. Fung, Deep neural network technique for automated detection of ADHD and CD using ECG signal, Comput. Methods Programs Biomed. 241 (2023) 107775, http://dx.doi.org/10.1016/j.cmpb.2023.107775, URL https://www.sciencedirect.com/science/article/pii/S0169260723004418.

[183] O. Faust, W. Hong, H.W. Loh, S. Xu, R.-S. Tan, S. Chakraborty, P.D. Barua, F. Molinari, U.R. Acharya, Heart rate variability for medical decision support systems: A review, Comput. Biol. Med. 145 (2022) 105407.

[184] H.W. Loh, S. Xu, O. Faust, C.P. Ooi, P.D. Barua, S. Chakraborty, R.-S. Tan, F. Molinari, U.R. Acharya, Application of photoplethysmography signals for healthcare systems: An in-depth review, Comput. Methods Programs Biomed. 216 (2022) 106677.

[185] J. Zhou, G. Fang, N. Wu, Survey on security and privacy-preserving in federated learning, J. Xihua Univ. (Nat. Sci. Ed.) 39 (4) (2020) 9–17.

[186] F. Liu, M. Li, X. Liu, T. Xue, J. Ren, C. Zhang, A review of federated meta-learning and its application in cyberspace security, Electronics 12 (15) (2023) 3295.

[187] A. Noore, R. Singh, M. Vasta, Fusion, sensor-level, in: S.Z. Li, A. Jain (Eds.), Encyclopedia of Biometrics, Springer US, Boston, MA, 2009, pp. 616–621, http://dx.doi.org/10.1007/978-0-387-73003-5_156.

[188] A. Ross, Fusion, feature-level, in: S.Z. Li, A. Jain (Eds.), Encyclopedia of Biometrics, Springer US, Boston, MA, 2009, pp. 597–602, http://dx.doi.org/10.1007/978-0-387-73003-5_157.

[189] L. Osadciw, K. Veeramachaneni, Fusion, decision-level, in: S.Z. Li, A. Jain (Eds.), Encyclopedia of Biometrics, Springer US, Boston, MA, 2009, pp. 593–597, http://dx.doi.org/10.1007/978-0-387-73003-5_160.

[190] H.A. Ignatious, H. El-Sayed, P. Kulkarni, Multilevel data and decision fusion using heterogeneous sensory data for autonomous vehicles, Remote Sens. 15 (9) (2023) http://dx.doi.org/10.3390/rs15092256, URL https://www.mdpi.com/2072-4292/15/9/2256.

[191] Y. Cimtay, E. Ekmekcioglu, S. Caglar-Ozhan, Cross-subject multimodal emotion recognition based on hybrid fusion, IEEE Access 8 (2020) 168865–168878, http://dx.doi.org/10.1109/ACCESS.2020.3023871.

[192] Y. Tan, Z. Sun, F. Duan, J. Solé-Casals, C.F. Caiafa, A multimodal emotion recognition method based on facial expressions and electroencephalography, Biomed. Signal Process. Control 70 (2021) 103029, http://dx.doi.org/10.1016/j.bspc.2021.103029, URL https://www.sciencedirect.com/science/article/pii/S1746809421006261.

[193] S.K. Khare, U.R. Acharya, Adazd-Net: Automated adaptive and explainable Alzheimer's disease detection system using EEG signals, Knowl.-Based Syst. (2023) 110858, http://dx.doi.org/10.1016/j.knosys.2023.110858, URL https://www.sciencedirect.com/science/article/pii/S0950705123006081.

[194] M. Abdar, F. Pourpanah, S. Hussain, D. Rezazadegan, L. Liu, M. Ghavamzadeh, P. Fieguth, X. Cao, A. Khosravi, U.R. Acharya, et al., A review of uncertainty quantification in deep learning: Techniques, applications and challenges, Inf. Fusion 76 (2021) 243–297.

[195] R. Alizadehsani, M. Roshanzamir, S. Hussain, A. Khosravi, A. Koohestani, M.H. Zangooei, M. Abdar, A. Beykikhoshk, A. Shoeibi, A. Zare, et al., Handling of uncertainty in medical data using machine learning and probability theory techniques: A review of 30 years (1991–2020), Ann. Oper. Res. (2021) 1–42.

[196] S. Seoni, V. Jahmunah, M. Salvi, P.D. Barua, F. Molinari, U.R. Acharya, Application of uncertainty quantification to artificial intelligence in healthcare: A review of last decade (2013–2023), Comput. Biol. Med. (2023) 107441, http://dx.doi.org/10.1016/j.compbiomed.2023.107441, URL https://www.sciencedirect.com/science/article/pii/S001048252300906X.

[197] G. Dandy, W. Wu, A. Simpson, M. Leonard, A review of sources of uncertainty in optimization objectives of water distribution systems, Water 15 (1) (2023) http://dx.doi.org/10.3390/w15010136, URL https://www.mdpi.com/2073-4441/15/1/136.

[198] V. Jahmunah, E. Ng, R.-S. Tan, S.L. Oh, U.R. Acharya, Uncertainty quantification in DenseNet model using myocardial infarction ECG signals, Comput. Methods Programs Biomed. 229 (2023) 107308.

[199] S. Taran, V. Bajaj, Emotion recognition from single-channel EEG signals using a two-stage correlation and instantaneous frequency-based filtering method, Comput. Methods Programs Biomed. 173 (2019) 157–165, http://dx.doi.org/10.1016/j.cmpb.2019.03.015, URL https://www.sciencedirect.com/science/article/pii/S016926071930118X.

[200] R. Jenke, A. Peer, M. Buss, Feature extraction and selection for emotion recognition from EEG, IEEE Trans. Affect. Comput. 5 (3) (2014) 327–339, http://dx.doi.org/10.1109/TAFFC.2014.2339834.
[201] X. Li, D. Song, P. Zhang, Y. Zhang, Y. Hou, B. Hu, Exploring EEG features in cross-subject emotion recognition, Front. Neurosci. 12 (2018) http://dx.doi.org/10.3389/fnins.2018.00162, URL https://www.frontiersin.org/articles/10.3389/fnins.2018.00162.
[202] H. Chao, L. Dong, Y. Liu, B. Lu, Emotion recognition from multiband EEG signals using CapsNet, Sensors 19 (9) (2019) http://dx.doi.org/10.3390/s19092212, URL https://www.mdpi.com/1424-8220/19/9/2212.
[203] X. Xing, Z. Li, T. Xu, L. Shu, B. Hu, X. Xu, SAE+LSTM: A new framework for emotion recognition from multi-channel EEG, Front. Neurorobot. 13 (2019) http://dx.doi.org/10.3389/fnbot.2019.00037, URL https://www.frontiersin.org/articles/10.3389/fnbot.2019.00037.
[204] T. Song, W. Zheng, P. Song, Z. Cui, EEG emotion recognition using dynamical graph convolutional neural networks, IEEE Trans. Affect. Comput. 11 (3) (2020) 532–541, http://dx.doi.org/10.1109/TAFFC.2018.2817622.
[205] Y. Cimtay, E. Ekmekcioglu, Investigating the use of pretrained convolutional neural network on cross-subject and cross-dataset EEG emotion recognition, Sensors 20 (7) (2020) http://dx.doi.org/10.3390/s20072034, URL https://www.mdpi.com/1424-8220/20/7/2034.
[206] P. Zhong, D. Wang, C. Miao, EEG-based emotion recognition using regularized graph neural networks, IEEE Trans. Affect. Comput. 13 (3) (2022) 1290–1301, http://dx.doi.org/10.1109/TAFFC.2020.2994159.
[207] W.-L. Zheng, B.-L. Lu, Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks, IEEE Trans. Auton. Ment. Dev. 7 (3) (2015) 162–175, http://dx.doi.org/10.1109/TAMD.2015.2431497.
[208] J.X. Chen, P.W. Zhang, Z.J. Mao, Y.F. Huang, D.M. Jiang, Y.N. Zhang, Accurate EEG-based emotion recognition on combined features using deep convolutional neural networks, IEEE Access 7 (2019) 44317–44328, http://dx.doi.org/10.1109/ACCESS.2019.2908285.
[209] J. Cheng, M. Chen, C. Li, Y. Liu, R. Song, A. Liu, X. Chen, Emotion recognition from multi-channel EEG via deep forest, IEEE J. Biomed. Health Inf. 25 (2) (2021) 453–464, http://dx.doi.org/10.1109/JBHI.2020.2995767.
[210] W. Tao, C. Li, R. Song, J. Cheng, Y. Liu, F. Wan, X. Chen, EEG-based emotion recognition via channel-wise attention and self attention, IEEE Trans. Affect. Comput. 14 (1) (2023) 382–393, http://dx.doi.org/10.1109/TAFFC.2020.3025777.
[211] F. Yang, X. Zhao, W. Jiang, P. Gao, G. Liu, Multi-method fusion of cross-subject emotion recognition based on high-dimensional EEG features, Front. Comput. Neurosci. 13 (2019) http://dx.doi.org/10.3389/fncom.2019.00053, URL https://www.frontiersin.org/articles/10.3389/fncom.2019.00053.
[212] Q. Gao, C.-h. Wang, Z. Wang, X.-l. Song, E.-z. Dong, Y. Song, EEG based emotion recognition using fusion feature extraction method, Multimedia Tools Appl. 79 (2020) 27057–27074.
[213] Y. Peng, F. Qin, W. Kong, Y. Ge, F. Nie, A. Cichocki, GFIL: A unified framework for the importance analysis of features, frequency bands, and channels in EEG-based emotion recognition, IEEE Trans. Cogn. Dev. Syst. 14 (3) (2022) 935–947, http://dx.doi.org/10.1109/TCDS.2021.3082803.
[214] R. Nawaz, K.H. Cheah, H. Nisar, V.V. Yap, Comparison of different feature extraction methods for EEG-based emotion recognition, Biocybern. Biomed. Eng. 40 (3) (2020) 910–926, http://dx.doi.org/10.1016/j.bbe.2020.04.005, URL https://www.sciencedirect.com/science/article/pii/S0208521620300553.
[215] A. Mert, A. Akan, Emotion recognition from EEG signals by using multivariate empirical mode decomposition, Pattern Anal. Appl. 21 (2018) 81–89.
[216] J. Zhang, M. Chen, S. Zhao, S. Hu, Z. Shi, Y. Cao, ReliefF-based EEG sensor selection methods for emotion recognition, Sensors 16 (10) (2016) http://dx.doi.org/10.3390/s16101558, URL https://www.mdpi.com/1424-8220/16/10/1558.
[217] D. Maheshwari, S. Ghosh, R. Tripathy, M. Sharma, U.R. Acharya, Automated accurate emotion recognition system using rhythm-specific deep convolutional neural network technique with multi-channel EEG signals, Comput. Biol. Med. 134 (2021) 104428, http://dx.doi.org/10.1016/j.compbiomed.2021.104428, URL https://www.sciencedirect.com/science/article/pii/S0010482521002225.
[218] H. Uyanık, S.T.A. Ozcelik, Z.B. Duranay, A. Sengur, U.R. Acharya, Use of differential entropy for automated emotion recognition in a virtual reality environment with EEG signals, Diagnostics 12 (10) (2022) http://dx.doi.org/10.3390/diagnostics12102508, URL https://www.mdpi.com/2075-4418/12/10/2508.
[219] M.B.H. Wiem, Z. Lachiri, Emotion classification in arousal valence model using MAHNOB-HCI database, Int. J. Adv. Comput. Sci. Appl. 8 (3) (2017).
[220] Z. Wang, X. Zhou, W. Wang, C. Liang, Emotion recognition using multimodal deep learning in multiple psychophysiological signals and video, Int. J. Mach. Learn. Cybern. 11 (4) (2020) 923–934.
[221] D.B. Setyohadi, S. Kusrohmaniah, S.B. Gunawan, P. Pranowo, Galvanic skin response data classification for emotion detection, Int. J. Electr. Comput. Eng. (IJECE) 8 (5) (2018) 31–41.
[222] S. Dutta, B.K. Mishra, A. Mitra, A. Chakraborty, An analysis of emotion recognition based on GSR signal, ECS Trans. 107 (1) (2022) 12535.
[223] J.Z. Lim, J. Mountstephens, J. Teo, Exploring pupil position as an eye-tracking feature for four-class emotion classification in VR, J. Phys. Conf. Ser. 2129 (1) (2021) 012069, http://dx.doi.org/10.1088/1742-6596/2129/1/012069.
[224] P. Tarnowski, M. Kołodziej, A. Majkowski, R. Rak, Eye-tracking analysis for emotion recognition, Comput. Intell. Neurosci. 2020 (2020) 1–13, http://dx.doi.org/10.1155/2020/2909267.
[225] Q. Wu, N. Dey, F. Shi, R.G. Crespo, R.S. Sherratt, Emotion classification on eye-tracking and electroencephalograph fused signals employing deep gradient neural networks, Appl. Soft Comput. 110 (2021) 107752, http://dx.doi.org/10.1016/j.asoc.2021.107752, URL https://www.sciencedirect.com/science/article/pii/S1568494621006736.
[226] S. Demircan, H. Kahramanli Örnek, Feature extraction from speech data for emotion recognition, J. Adv. Comput. Netw. 2 (2014) 28–30, http://dx.doi.org/10.7763/JACN.2014.V2.76.
[227] L. Sun, B. Zou, S. Fu, J. Chen, F. Wang, Speech emotion recognition based on DNN-decision tree SVM model, Speech Commun. 115 (2019) 29–37, http://dx.doi.org/10.1016/j.specom.2019.10.004, URL https://www.sciencedirect.com/science/article/pii/S016763931930127X.
[228] P. Krishnan, A.N. Joseph Raj, V. R, Emotion classification from speech signal based on empirical mode decomposition and non-linear features, Complex Intell. Syst. 7 (2021) 1919–1934, http://dx.doi.org/10.1007/s40747-021-00295-z.
[229] H.M. Fayek, M. Lech, L. Cavedon, Evaluating deep learning architectures for speech emotion recognition, Neural Netw. 92 (2017) 60–68, http://dx.doi.org/10.1016/j.neunet.2017.02.013, Advances in Cognitive Engineering Using Neural Networks. URL https://www.sciencedirect.com/science/article/pii/S089360801730059X.
[230] D. Tanko, S. Dogan, F. Burak Demir, M. Baygin, S. Engin Sahin, T. Tuncer, Shoelace pattern-based speech emotion recognition of the lecturers in distance education: ShoePat23, Appl. Acoust. 190 (2022) 108637, http://dx.doi.org/10.1016/j.apacoust.2022.108637, URL https://www.sciencedirect.com/science/article/pii/S0003682X22000111.
[231] Z.-T. Liu, M. Wu, W.-H. Cao, J.-W. Mao, J.-P. Xu, G.-Z. Tan, Speech emotion recognition based on feature selection and extreme learning machine decision tree, Neurocomputing 273 (2018) 271–280, http://dx.doi.org/10.1016/j.neucom.2017.07.050, URL https://www.sciencedirect.com/science/article/pii/S0925231217313565.
[232] T. Tuncer, S. Dogan, U.R. Acharya, Automated accurate speech emotion recognition system using twine shuffle pattern and iterative neighborhood component analysis techniques, Knowl.-Based Syst. 211 (2021) 106547, http://dx.doi.org/10.1016/j.knosys.2020.106547, URL https://www.sciencedirect.com/science/article/pii/S0950705120306766.
[233] Z. ullah, L. Qi, D. Binu, B.R. Rajakumar, B. Mohammed Ismail, 2-D canonical correlation analysis based image super-resolution scheme for facial emotion recognition, Multimedia Tools Appl. 81 (10) (2022) 13911–13934, http://dx.doi.org/10.1007/s11042-022-11922-3.
[234] H. Li, H. Xu, Deep reinforcement learning for robust emotional classification in facial expression recognition, Knowl.-Based Syst. 204 (2020) 106172, http://dx.doi.org/10.1016/j.knosys.2020.106172, URL https://www.sciencedirect.com/science/article/pii/S0950705120304081.
[235] K. Chowdary, T. Nguyen, D. Hemanth, Deep learning-based facial emotion recognition for human–computer interaction applications, Neural Comput. Appl. (2021) 1–18, http://dx.doi.org/10.1007/s00521-021-06012-8.
[236] D.K. Jain, P. Shamsolmoali, P. Sehdev, Extended deep neural network for facial emotion recognition, Pattern Recognit. Lett. 120 (2019) 69–74, http://dx.doi.org/10.1016/j.patrec.2019.01.008, URL https://www.sciencedirect.com/science/article/pii/S016786551930008X.
[237] F. Zhang, T. Zhang, Q. Mao, C. Xu, Geometry guided pose-invariant facial expression recognition, IEEE Trans. Image Process. 29 (2020) 4445–4460, http://dx.doi.org/10.1109/TIP.2020.2972114.
[238] H. Zhang, A. Jolfaei, M. Alazab, A face emotion recognition method using convolutional neural network and image edge computing, IEEE Access 7 (2019) 159081–159089, http://dx.doi.org/10.1109/ACCESS.2019.2949741.
[239] N.D. Mehendale, Facial emotion recognition using convolutional neural networks (FERC), SN Appl. Sci. 2 (2020) 1–8.
[240] R. Kumar, S. Muniasamy, N. Arumugam, Facial emotion recognition using subband selective multilevel stationary wavelet gradient transform and fuzzy support vector machine, Vis. Comput. 37 (2021) 1–15, http://dx.doi.org/10.1007/s00371-020-01988-1.
[241] Y.-D. Zhang, Z.-J. Yang, H.-M. Lu, X.-X. Zhou, P. Phillips, Q.-M. Liu, S.-H. Wang, Facial emotion recognition based on biorthogonal wavelet entropy, fuzzy support vector machine, and stratified cross validation, IEEE Access 4 (2016) 8375–8385, http://dx.doi.org/10.1109/ACCESS.2016.2628407.
[242] K. Sarvakar, R. Senkamalavalli, S. Raghavendra, J. Santosh Kumar, R. Manjunath, S. Jaiswal, Facial emotion recognition using convolutional neural networks, Mater. Today: Proc. 80 (2023) 3560–3564, http://dx.doi.org/10.1016/j.matpr.2021.07.297, SI:5 NANO 2021. URL https://www.sciencedirect.com/science/article/pii/S2214785321051567.
[243] S. Zhao, H. Yao, Y. Gao, R. Ji, G. Ding, Continuous probability distribution prediction of image emotions via multitask shared sparse regression, IEEE Trans. Multimed. 19 (3) (2017) 632–645, http://dx.doi.org/10.1109/TMM.2016.2617741.

[244] S. Katsigiannis, N. Ramzan, DREAMER: A database for emotion recognition through EEG and ECG signals from wireless low-cost off-the-shelf devices, IEEE J. Biomed. Health Inf. 22 (1) (2018) 98–107, http://dx.doi.org/10.1109/JBHI.2017.2688239.

[245] R.-N. Duan, J.-Y. Zhu, B.-L. Lu, Differential entropy feature for EEG-based emotion classification, in: 6th International IEEE/EMBS Conference on Neural Engineering (NER), IEEE, 2013, pp. 81–84.

[246] S. Sangnark, P. Autthasan, P. Ponglertnapakorn, P. Chalekarn, T. Sudhawiyangkul, M. Trakulruangroj, S. Songsermsawad, R. Assabumrungrat, S. Amplod, K. Ounjai, T. Wilaiprasitporn, Revealing preference in popular music through familiarity and brain response, IEEE Sens. J. (2021) 1.

[247] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, I. Patras, DEAP: A database for emotion analysis using physiological signals, IEEE Trans. Affect. Comput. 3 (1) (2012) 18–31, http://dx.doi.org/10.1109/T-AFFC.2011.15.

[248] P. Lakhan, N. Banluesombatkul, V. Changniam, R. Dhithijaiyratn, P. Leelaarporn, E. Boonchieng, S. Hompoonsup, T. Wilaiprasitporn, Consumer grade brain sensing for emotion recognition, IEEE Sens. J. 19 (21) (2019) 9896–9907, http://dx.doi.org/10.1109/JSEN.2019.2928781.

[249] E. Ekmekcioglu, Y. Cimtay, Loughborough university multimodal emotion dataset-2, 2021, http://dx.doi.org/10.6084/m9.figshare.12644033.v5, URL https://figshare.com/articles/dataset/Loughborough_University_Multimodal_Emotion_Dataset_-_2/12644033.

[250] W. Zheng, W. Liu, Y. Lu, B. Lu, A. Cichocki, EmotionMeter: A multimodal framework for recognizing human emotions, IEEE Trans. Cybern. (2018) 1–13, http://dx.doi.org/10.1109/TCYB.2018.2797176.

[251] M. Soleymani, J. Lichtenauer, T. Pun, M. Pantic, A multimodal database for affect recognition and implicit tagging, IEEE Trans. Affect. Comput. 3 (1) (2012) 42–55, http://dx.doi.org/10.1109/T-AFFC.2011.25.

[252] G. Zhao, Y. Zhang, Y. Ge, Y. Zheng, X. Sun, K. Zhang, Asymmetric hemisphere activation in tenderness: evidence from EEG signals, Sci. Rep. 8 (1) (2018) 8029.

[253] G. Zhao, Y. Zhang, Y. Ge, Frontal EEG asymmetry and middle line power difference in discrete emotions, Front. Behav. Neurosci. 12 (2018) 225.

[254] J.A. Miranda-Correa, M.K. Abadi, N. Sebe, I. Patras, AMIGOS: A dataset for affect, personality and mood research on individuals and groups, IEEE Trans. Affect. Comput. 12 (2) (2021) 479–493, http://dx.doi.org/10.1109/TAFFC.2018.2884461.

[255] T.B. Alakus, M. Gonen, I. Turkoglu, Database for an emotion recognition system based on EEG signals and various computer games - GAMEEMO, Biomed. Signal Process. Control 60 (2020) 101951, http://dx.doi.org/10.1016/j.bspc.2020.101951, URL https://www.sciencedirect.com/science/article/pii/S1746809420301075.

[256] T. Song, W. Zheng, C. Lu, Y. Zong, X. Zhang, Z. Cui, MPED: A multi-modal physiological emotion database for discrete emotion recognition, IEEE Access 7 (2019) 12177–12191, http://dx.doi.org/10.1109/ACCESS.2019.2891579.

[257] R. Subramanian, J. Wache, M.K. Abadi, R.L. Vieriu, S. Winkler, N. Sebe, ASCERTAIN: emotion and personality recognition using commercial sensors, IEEE Trans. Affect. Comput. 9 (2) (2018) 147–160, http://dx.doi.org/10.1109/TAFFC.2016.2625250.

[258] A. Baghdadi, Y. Aribi, R. Fourati, N. Halouani, P. Siarry, A.M. Alimi, DASPS: A database for anxious states based on a psychological stimulation, 2019, arXiv:1901.02942.

[259] M. Yu, S. Xiao, M. Hua, H. Wang, X. Chen, F. Tian, Y. Li, EEG-based emotion recognition in an immersive virtual reality environment: From local activity to brain network features, Biomed. Signal Process. Control 72 (2022) 103349, http://dx.doi.org/10.1016/j.bspc.2021.103349, URL https://www.sciencedirect.com/science/article/pii/S1746809421009460.

[260] R. Ivanov, F. Kazantsev, E. Zavarzin, A. Klimenko, N. Milakhina, Y.G. Matushkin, A. Savostyanov, S. Lashin, ICBrainDB.: an integrated database for finding associations between genetic factors and EEG markers of depressive disorders, J. Pers. Med. 12 (1) (2022) 53.

[261] J. Wagner, J. Kim, E. Andre, From physiological signals to emotions: Implementing and comparing selected methods for feature extraction and classification, in: 2005 IEEE International Conference on Multimedia and Expo, 2005, pp. 940–943, http://dx.doi.org/10.1109/ICME.2005.1521579.

[262] P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, K. Van Laerhoven, Introducing WESAD, a multimodal dataset for wearable stress and affect detection, in: Proceedings of the 20th ACM International Conference on Multimodal Interaction, ICMI '18, Association for Computing Machinery, New York, NY, USA, 2018, pp. 400–408, http://dx.doi.org/10.1145/3242969.3242985.

[263] L. Zhang, S. Walter, X. Ma, P. Werner, A. Al-Hamadi, H.C. Traue, S. Gruss, "BioVid Emo DB": A multimodal database for emotion analyses validated by subjective ratings, in: 2016 IEEE Symposium Series on Computational Intelligence (SSCI), 2016, pp. 1–6, http://dx.doi.org/10.1109/SSCI.2016.7849931.

[264] S. Koldijk, M. Sappelli, S. Verberne, M.A. Neerincx, W. Kraaij, The SWELL knowledge work dataset for stress and user modeling research, in: Proceedings of the 16th International Conference on Multimodal Interaction, ICMI '14, Association for Computing Machinery, New York, NY, USA, 2014, pp. 291–298, http://dx.doi.org/10.1145/2663204.2663257.

[265] J.-H. Maeng, D.-H. Kang, D.-H. Kim, Deep learning method for selecting effective models and feature groups in emotion recognition using an Asian multimodal database, Electronics 9 (12) (2020) http://dx.doi.org/10.3390/electronics9121988, URL https://www.mdpi.com/2079-9292/9/12/1988.

[266] S.R. Livingstone, F.A. Russo, The Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS): A dynamic, multimodal set of facial and vocal expressions in North American English, PLOS ONE 13 (5) (2018) 1–35, http://dx.doi.org/10.1371/journal.pone.0196391.

[267] E. Chen, Z. Lu, H. Xu, L. Cao, Y. Zhang, J. Fan, A large scale speech sentiment corpus, in: Proceedings of the Twelfth Language Resources and Evaluation Conference, European Language Resources Association, Marseille, France, 2020, pp. 6549–6555, URL https://aclanthology.org/2020.lrec-1.806.

[268] C. Busso, M. Bulut, C.-C. Lee, A. Kazemzadeh, E. Mower, S. Kim, J.N. Chang, S. Lee, S.S. Narayanan, IEMOCAP: Interactive emotional dyadic motion capture database, Lang. Resour. Eval. 42 (2008) 335–359.

[269] F. Burkhardt, A. Paeschke, M. Rolfes, W.F. Sendlmeier, B. Weiss, et al., A database of German emotional speech, in: Interspeech, Vol. 5, 2005, pp. 1517–1520.

[270] A. Dhall, R. Goecke, S. Lucey, T. Gedeon, Collecting large, richly annotated facial-expression databases from movies, IEEE MultiMedia 19 (3) (2012) 34–41, http://dx.doi.org/10.1109/MMUL.2012.26.

[271] W. Bao, Y. Li, M. Gu, M. Yang, H. Li, L. Chao, J. Tao, Building a Chinese natural emotional audio-visual database, in: 2014 12th International Conference on Signal Processing (ICSP), 2014, pp. 583–587, http://dx.doi.org/10.1109/ICOSP.2014.7015071.

[272] K. Wang, Q. Zhang, S. Liao, A database of elderly emotional speech, in: Proc. Int. Symp. Signal Process. Biomed. Eng Informat, 2014, pp. 549–553.

[273] S.G. Koolagudi, R. Reddy, J. Yadav, K.S. Rao, IITKGP-SEHSC : Hindi speech corpus for emotion analysis, in: 2011 International Conference on Devices and Communications (ICDeCom), 2011, pp. 1–5, http://dx.doi.org/10.1109/ICDECOM.2011.5738540.

[274] O. Martin, I. Kotsia, B. Macq, I. Pitas, The eNTERFACE' 05 audio-visual emotion database, in: 22nd International Conference on Data Engineering Workshops (ICDEW'06), 2006, p. 8, http://dx.doi.org/10.1109/ICDEW.2006.145.

[275] T. Bänziger, M. Mortillaro, K.R. Scherer, Introducing the Geneva Multimodal expression corpus for experimental research on emotion perception, Emotion 12 (5) (2012) 1161.

[276] S. Haq, P. Jackson, Speaker-dependent audio-visual emotion recognition, in: Proc. Int. Conf. on Auditory-Visual Speech Processing (AVSP'08), Norwich, UK, 2009.

[277] S. Haq, P. Jackson, in: W. Wang (Ed.), Machine Audition: Principles, Algorithms and Systems, IGI Global, Hershey PA, 2010, pp. 398–423, Ch. Multimodal Emotion Recognition.

[278] S. Haq, P. Jackson, J. Edge, Audio-visual feature selection and reduction for emotion classification, in: Proc. Int. Conf. on Auditory-Visual Speech Processing (AVSP'08), Tangalooma, Australia, 2008.

[279] A. Batliner, S. Steidl, E. Nöth, Releasing a thoroughly annotated and processed spontaneous emotional database: the FAU Aibo Emotion Corpus, 2008.

[280] M.K. Pichora-Fuller, K. Dupuis, Toronto emotional speech set (TESS), 2020, http://dx.doi.org/10.5683/SP2/E8H2MF.

[281] S. Zhalehpour, O. Onder, Z. Akhtar, C.E. Erdem, BAUM-1: A spontaneous audio-visual face database of affective and mental states, IEEE Trans. Affect. Comput. 8 (3) (2017) 300–313, http://dx.doi.org/10.1109/TAFFC.2016.2553038.

[282] Y. Wang, L. Guan, Recognizing human emotional state from audiovisual signals, IEEE Trans. Multimed. 10 (5) (2008) 936–946, http://dx.doi.org/10.1109/TMM.2008.927665.

[283] G. Costantini, I. Iaderola, A. Paoloni, M. Todisco, EMOVO corpus: an Italian emotional speech database, in: Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14), European Language Resources Association (ELRA), Reykjavik, Iceland, 2014, pp. 3501–3504, URL http://www.lrec-conf.org/proceedings/lrec2014/pdf/591_Paper.pdf.

[284] D. Lundqvist, A. Flykt, A. Öhman, Karolinska directed emotional faces, Cogn. Emot. (1998).

[285] P. Lucey, J.F. Cohn, T. Kanade, J. Saragih, Z. Ambadar, I. Matthews, The Extended Cohn-Kanade Dataset (CK+): A complete dataset for action unit and emotion-specified expression, in: 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops, 2010, pp. 94–101, http://dx.doi.org/10.1109/CVPRW.2010.5543262.

[286] M. Lyons, S. Akamatsu, M. Kamachi, J. Gyoba, Coding facial expressions with Gabor wavelets, in: Proceedings Third IEEE International Conference on Automatic Face and Gesture Recognition, 1998, pp. 200–205, http://dx.doi.org/10.1109/AFGR.1998.670949.

[287] R. Gross, I. Matthews, J. Cohn, T. Kanade, S. Baker, Multi-PIE, in: 2008 8th IEEE International Conference on Automatic Face & Gesture Recognition, 2008, pp. 1–8, http://dx.doi.org/10.1109/AFGR.2008.4813399.

[288] R. Gross, I. Matthews, J. Cohn, T. Kanade, S. Baker, Multi-PIE, Image Vis. Comput. 28 (5) (2010) 807–813, http://dx.doi.org/10.1016/j.imavis.2009.08.002, Best of Automatic Face and Gesture Recognition 2008. URL https://www.sciencedirect.com/science/article/pii/S0262885609001711.

[289] A. Mollahosseini, B. Hasani, M.H. Mahoor, AffectNet: A database for facial expression, valence, and arousal computing in the wild, IEEE Trans. Affect. Comput. 10 (1) (2019) 18–31, http://dx.doi.org/10.1109/TAFFC.2017.2740923.

[290] I.J. Goodfellow, D. Erhan, P.L. Carrier, A. Courville, M. Mirza, B. Hamner, W. Cukierski, Y. Tang, D. Thaler, D.-H. Lee, et al., Challenges in representation learning: A report on three machine learning contests, in: Neural Information Processing: 20th International Conference, ICONIP 2013, Daegu, Korea, November 3-7, 2013. Proceedings, Part III 20, Springer, 2013, pp. 117–124.

[291] M. Pantic, M. Valstar, R. Rademaker, L. Maat, Web-based database for facial expression analysis, in: 2005 IEEE International Conference on Multimedia and Expo, 2005, p. 5, http://dx.doi.org/10.1109/ICME.2005.1521424.

[292] S. Li, W. Deng, J. Du, Reliable crowdsourcing and deep locality-preserving learning for expression recognition in the wild, in: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, 2017, pp. 2584–2593.

[293] S. Li, W. Deng, Reliable crowdsourcing and deep locality-preserving learning for unconstrained facial expression recognition, IEEE Trans. Image Process. 28 (1) (2019) 356–370.

[294] Z. Zhang, P. Luo, C.C. Loy, X. Tang, From facial expression recognition to interpersonal relation prediction, Int. J. Comput. Vis. 126 (2018) 550–569.

[295] N. Aifanti, C. Papachristou, A. Delopoulos, The MUG facial expression database, in: 11th International Workshop on Image Analysis for Multimedia Interactive Services WIAMIS 10, 2010, pp. 1–4.

[296] D. Aneja, A. Colburn, G. Faigin, L. Shapiro, B. Mones, Modeling stylized character expressions via deep learning, in: Computer Vision–ACCV 2016: 13th Asian Conference on Computer Vision, Taipei, Taiwan, November 20-24, 2016, Revised Selected Papers, Part II 13, Springer, 2017, pp. 136–153.

[297] A. Dhall, R. Goecke, S. Lucey, T. Gedeon, Static facial expression analysis in tough conditions: Data, evaluation protocol and benchmark, in: 2011 IEEE International Conference on Computer Vision Workshops (ICCV Workshops), 2011, pp. 2106–2112, http://dx.doi.org/10.1109/ICCVW.2011.6130508.

[298] L. Yin, X. Wei, Y. Sun, J. Wang, M. Rosato, A 3D facial expression database for facial behavior research, in: 7th International Conference on Automatic Face and Gesture Recognition (FGR06), 2006, pp. 211–216, http://dx.doi.org/10.1109/FGR.2006.6.

[299] G.B. Huang, M. Mattar, T. Berg, E. Learned-Miller, Labeled faces in the wild: A database forstudying face recognition in unconstrained environments, in: Workshop on Faces in'Real-Life'Images: Detection, Alignment, and Recognition, 2008.

[300] G. Zhao, X. Huang, M. Taini, S.Z. Li, M. Pietikäinen, Facial expression recognition from near-infrared videos, Image Vis. Comput. 29 (9) (2011) 607–619, http://dx.doi.org/10.1016/j.imavis.2011.07.002, URL https://www.sciencedirect.com/science/article/pii/S0262885611000515.

[301] C.I. Watson, NIST special database 18. NIST Mugshot Identification Database (MID), 2008.

[302] F. Wallhoff, B. Schuller, M. Hawellek, G. Rigoll, Efficient recognition of authentic dynamic facial expressions on the feedtum database, in: 2006 IEEE International Conference on Multimedia and Expo, 2006, pp. 493–496, http://dx.doi.org/10.1109/ICME.2006.262433.

[303] Q. You, J. Luo, H. Jin, J. Yang, Building a large scale dataset for image emotion recognition: The fine print and the benchmark, in: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 30, 2016.

[304] O. Langner, R. Dotsch, G. Bijlstra, D.H. Wigboldus, S.T. Hawk, A. Van Knippenberg, Presentation and validation of the Radboud Faces Database, Cogn. Emot. 24 (8) (2010) 1377–1388.

[305] P. Lucey, J.F. Cohn, K.M. Prkachin, P.E. Solomon, I. Matthews, Painful data: The UNBC-McMaster shoulder pain expression archive database, in: 2011 IEEE International Conference on Automatic Face & Gesture Recognition (FG), 2011, pp. 57–64, http://dx.doi.org/10.1109/FG.2011.5771462.