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Survey Paper

Toward cross-subject and cross-session generalization in EEG-based emotion recognition: Systematic review, taxonomy, and methods[☆]

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ABSTRACT

A systematic review on machine-learning strategies for improving generalization in electroencephalography-based emotion classification was realized. In particular, cross-subject and cross-session generalization was focused. In this context, the non-stationarity of electroencephalographic (EEG) signals is a critical issue and can lead to the *Dataset Shift* problem. Several architectures and methods have been proposed to address this issue, mainly based on transfer learning methods. In this review, 449 papers were retrieved from the *Scopus*, *IEEE Xplore* and *PubMed* databases through a search query focusing on modern machine learning techniques for generalization in EEG-based emotion assessment. Among these papers, 79 were found eligible based on their relevance to the problem. Studies lacking a specific cross-subject or cross-session validation strategy, or making use of other biosignals as support were excluded. On the basis of the selected papers' analysis, a taxonomy of the studies employing Machine Learning (ML) methods was proposed, together with a brief discussion of the different ML approaches involved. The studies reporting the best results in terms of average classification accuracy were identified, supporting that transfer learning methods seem to perform better than other approaches. A discussion is proposed on the impact of (i) the emotion theoretical models and (ii) psychological screening of the experimental sample on the classifier performances.

1. Introduction

Emotions play a primary role in learning, reasoning, decision-making, and communication. An increasing interest in emotions in the Information and Communication Technology (ICT) sector has led to the emergence of *affective computing*, focused on monitoring and predicting emotions to enhance human–computer interaction [1]. For instance, innovations like *affective loops* allowed to facilitate the implementation of adaptive human–machine interfaces [2]. Furthermore, new emotion monitoring systems find applications in healthcare, aiding in psychological disorder treatments, autism intervention, well-being improvement, and stress management [3–5].

Brain-Computer Interface (BCI) systems based on EEG signals have garnered increasing attention, evident in the exponential growth of research indexed on platforms like *Scopus* [6] (see Fig. 1). EEG-based Emotion Recognition (ER) has applications across several fields, from car driving and workplace environments to neuromarketing and entertainment [7–13]. In clinical settings, EEG aids for example in measuring sleep parameters, detecting epileptic seizures, and addressing autism spectrum disorders [14–17]. However, EEG signal processing faces challenges due to inherent variability among subjects and acquisition times (i.e. sessions), since the EEG signal is usually stochastic and stationary only for short intervals (generally ranging from a few seconds to minutes) [18–20]. More in detail, the EEG signal is not a Wide Sense Stationary signal [21]. This characteristic of non-stationarity implies a variation in the temporal and spectral characteristics of the EEG signal over time. This is an open issue in the literature leading to a loss of generalizability for classification systems across subjects (*inter-subject* task) and, for the same subject, across different sessions (*intra-subject* task, also known as *cross-session*) [22]. Machine Learning

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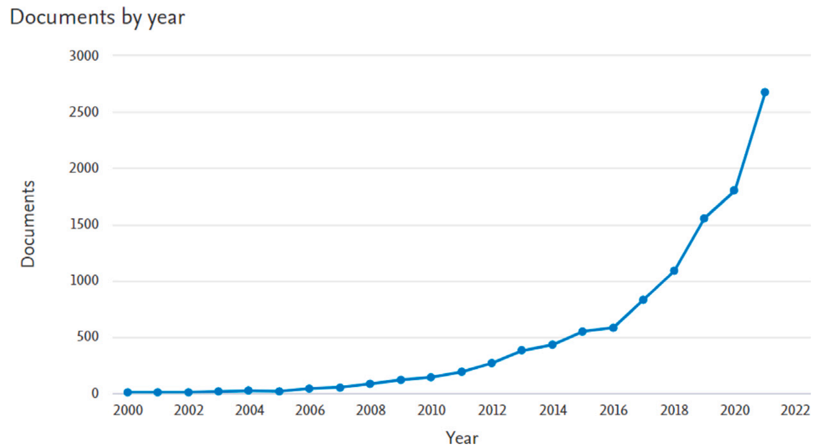

Fig. 1. Scopus trend for EEG-based emotion recognition studies.

(ML) methods are often employed to address these challenges, with an increasing trend toward deep neural networks and Transfer Learning-based approaches, such as domain adaptation, domain generalization and/or hybrid methods [23], enhancing generalizability across subjects and sessions. This paper provides a systematic review of ML techniques to enhance generalizability in EEG-based Emotion Recognition across different subjects and sessions. While previous surveys exist, none specifically focus on ML's role in inter/intra-subjective generalization in this domain.

The rest of the paper is organized as follows: Section 2 reviews related works, with reference to recent surveys carried out on this specific topic. Section 3 presents a theoretical background on EEG, with a first part focusing on BCIs for Emotion Recognition and a second part on ML for Emotion Recognition. Section 4 presents the used search queries and the paper selection process according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method [24]. Section 5 presents the results of the review, proposing a taxonomy of the ML methods currently proposed in the selected papers, discussing the ML methods with respect the proposed taxonomy. A statistical analyses of the results is also reported. Section 6 aims to discuss the achieved results, reporting the most promising lines of research and approaches, and highlighting current challenges and possible future directions in this area. Finally, Section 7 draws conclusions.

2. Related works

In recent years, several reviews have been conducted on generalization in EEG-based Emotion Recognition. Alarcao and Fonseca [25] focus on the generic topic of EEG-based Emotion Recognition, presenting a review of papers published in the period from 2009 to 2016. The survey appears interesting since it focused on the different stages of the Emotion Recognition process from EEG signals. Moreover, the survey proposed a criterion for assessing the quality of the papers by applying a set of well-known guidelines (Brouwer's recommendations [26]). However, there is no in-depth analysis on the issue of inter/intra-subject generalization, nor is the EEG-nonstationarity problem addressed. Other reviews [27,28] analyze studies on the EEG-based classification methods, but without focusing on the emotion domain. Wu et al. [28], offer a non-systematic review focusing on affective BCIs (aBCIs), but without an in-depth analysis of the Emotion Recognition problem. The study proposed in [29] defers further investigation of the problem of EEG-inter/intra-subject variability to future works. Recently, Li and colleagues [30] published a review focusing on the topic of EEG-based Emotion Recognition and discussing the importance of Transfer Learning. While offering some interesting results, it is not a systematic review (only 18 studies were reported without PRISMA methodology to collect them).

This paper proposed a systematic literature review focused on the inter/intra-subject generalization on EEG-based Emotion Recognition systems and the use of modern ML-based methods as a possible solution.

3. Theoretical background

3.1. Challenges in EEG cross-domain tasks

Cross-session and cross-subject tasks rely on different assumptions. In cross-session approaches, the EEG recordings are acquired from the same subject but at different times. In cross-subject approaches, data are acquired from different subjects. To date, a rigorous definition of the term *session* remains lacking. For instance, in the SEED documentation [31], the term was used interchangeably with *trial*, but the distinction was later reinstated in SEED IV. In addition, it is generally unclear what is the minimum time interval required between sessions, and if it is possible to conduct multiple sessions on the same day. Recently, the term *Cross-Day* have been adopted to specify sessions occurring in different days [32–34].

Three sources of uncertainty lead to generalization problems: (i) *measurand*, (ii) instrumentation (iii), and environment [35]. The uncertainty of the measurand is primarily caused by the non-stationarity of the EEG signal. However other factors have to be considered: (i) personal traits (personality, circadian rhythms, culture) [36], (ii) personal states (transient psychic conditions of the subject) [37], (iii) previous experiences (with the BCI in general or related to the specific stimuli used in the experimental set-up), and (iv) physical conditions (also dependent on recent physical stress or feeding in the previous hours [38]). The main sources of instrumental uncertainty concern the positioning of the electrodes [39] and the electrode–skin contact impedance. Humidity, temperature, brightness, noise pollution, and the ergonomics of the experimental station are sources of environmental uncertainty. They impact the signal by interacting with the measurand and the instrumentation [40]. Cross-subject tests are prone to all the uncertainties associated with the measurand. In contrast, cross-session tests are not influenced by personal traits, except for circadian rhythms when sessions are conducted at different times of the day. In Cross-Session tests, personal states, past experiences, and physical conditions keep on impacting. Past experiences may have a more pronounced impact if sessions are temporally close together, and a recently experienced experiment can bias the subsequent sessions. Personal state and physical conditions affect cross-session tests with a direct relation to time elapsed: the closer the sessions, the lower the expected variability. Sources of instrumental uncertainty come into play when equipment is taken off and put back on between sessions, as is the case of the cross-day paradigm. The effect of environmental factors can be influenced by the time gap between experimental activities. They could have more impact on two sessions conducted on different days with the same subject compared to measurements temporally close together involving different subjects. Additional sources of uncertainty need to be considered in cross-dataset problems [41], where (i) stimuli, (ii) measurement instrumentation, and (iii) experimental teams are different.

3.2. Generalization issues in BCI

Three fundamental paradigms of BCI can be distinguished: Active, Reactive, and Passive. *Active BCI* involves voluntary brainwave modulation, as seen in *Motor Imagery* (MI). It is generally expected that within MI, TL is easier to implement compared to ER, primarily due to the lower variability observed in MI tasks [42]. This reduced variability in neural patterns during MI activities can facilitate more straightforward adaptation from one subject to another or from one session to the next (e.g., [43]). Further insights and in-depth analysis about TL in MI can be found in [44]. *Reactive BCI* responds to external stimuli, such as *Event-Related Potential* (ERP)-based spellers. Already in 2014 a study demonstrated zero-training ERP spelling using Transfer Learning and language statistics [45], while [46] introduced a modular framework minimizing calibration time with Transfer Learning and Convolutional Neural Networks (CNNs). In [47] a TL method is proposed and validated on both MI and ERP datasets. Lastly, *passive BCI* involves users who do not directly or consciously manipulate their electrical brainwave patterns and focuses on monitoring (like Emotion Recognition). This review addresses generalization issues in this area.

3.3. Emotional theories

Various emotional theories coexist, notably the *discrete* and *dimensional* theories. The discrete theory, influenced by Darwinian tradition and exemplified by Ekman and Plutchik, identifies basic, universal and innate emotions [48]. Ekman delineates six (anger, disgust, fear, happiness, sadness, and surprise [49]), while Plutchik proposes eight (anger, anticipation, joy, trust, fear, surprise, sadness, and disgust) arranged on a wheel model [29]. Conversely, the dimensional theory represents emotions along valence-arousal or valence-arousal-dominance axes, emphasizing continuous dimensions of pleasantness, arousal, and dominance. Neurophysiological underpinnings are addressed differently; the dimensional theory identifies brain networks [50], while the discrete theory suggests dedicated neural circuits. The choice between these approaches depends on the intended focus in emotion assessment.

3.4. BCI for emotion recognition

Emotional states can recognized through various biosignals. Brain signals, particularly EEG, gaining prominence due to their high temporal resolution and non-invasiveness. EEG signals span a frequency range of [0.01, 100.00] Hz and an amplitude typically within [−100, 100] μV. They encompass five background rhythms classified into delta, theta, alpha, beta, and gamma bands.

The International 10–20 Positioning System is a standardized method for electrode placement used to retain consistency across experiments [51]. Electrode quality, whether wet or dry, impacts signal fidelity [52]. Wet electrodes use conductive gel in order to ensure electrode–skin contact, while in the case of dry electrodes, the contact surface is increased in order to facilitate the electrical contact [53].

The methods and stimuli for emotion induction significantly influence EEG-based emotion assessment. Techniques like film clips, images, and music effectively induce emotions, with images offering standardization advantages [54,55]. Established image datasets like IAPS [55], OASIS [56], and GAPED [57] facilitate emotion elicitation experiments. Publicly available EEG databases such as DEAP [58], SEED [31], and DREAMER [59] aid emotion recognition research. Each dataset contains different physiological signals and is characterized by a well-established experimental setup (Table 1). Self-produced datasets require meticulous preprocessing, including line noise removal, referencing, bad channel removal, and artifact correction [19]. Once the EEG signal has been pre-processed, it is usually divided into epochs, and a feature extraction process is then applied. EEG features can be categorized into three domains, namely (i) time, (ii) frequency, and (iii) time–frequency. Time domain features include signal statistics (such as mean, variance, skewness, kurtosis) [60–62], Hjorth parameters (namely Activity, Mobility, and Complexity) [63], entropy-based measures [64], and higher-order crossing [65]. Frequency domain features primarily utilize power spectral density [66], while time–frequency analysis employs methods like STFT, CWT, DWT, matching pursuit, and empirical mode decomposition [67,68].

Feature selection is critical due to the high dimensionality of EEG features [69]. Additionally, selecting informative EEG channels reduces computational complexity [70].

3.5. Machine learning for emotion recognition

After the EEG signal has been properly pre-processed and a suitable set of features has been extracted, the data are ready to be fed to a supervised ML system. The typical pipeline of a ML framework applied to an EEG Emotion Recognition task is reported in Fig. 2.

A large part of the current literature on Emotion Recognition proposed methods framed in the Transfer Learning approach. This is because in the classical supervised ML framework a set of already labeled data has to be available. This implies that, in EEG Emotion Recognition tasks, a set of EEG signals recorded from one or more subjects has to be labeled with the emotion felt during the acquisition. Labeled data can then be used to train the ML system, generating a ML model able to classify the input data. Once the ML model is obtained, new unlabeled data can be fed to the ML model to estimate the corresponding emotion/class. Reserving a portion of the labeled data outside the training stage to evaluate the trained model is a good practice. These data can then be used to evaluate the final model predictions using suitable performance metrics (e.g., accuracy). However, a standard hypothesis of traditional ML methods is that all available data come from the same probability distribution, no matter if involved in the training process or not. Due to the characteristics of the EEG data, this assumption results not always verified in the EEG signal. Indeed, the EEG recordings of different subjects can be strongly different from each other, even under the same conditions [19]. Strong differences can arise also for EEG recordings acquired from the same subject but in different times/sessions, leading to low generalization performance in cross-subject/session problems. In the current literature, this problem was initially addressed by exploiting additional unlabeled data belonging to the target subject/session during the training stage (Transductive Learning approaches). However, these methods do not make any consideration about the data distributions. In fact, the training EEG data may belong to significantly different probability distributions than the data used outside the training phase. In ML literature, this can be considered an instance of the Dataset Shift problem [71]. Dataset Shift occurs in an experimental environment where the standard ML assumption is not verified, i.e. the distributions of the training data and the data used outside the training stage may be different. The idea that data used inside and outside of training stage can belong to different probability distributions is the main hypothesis of the Transfer Learning approaches.

In the last years, several ML architectures and methods have been proposed to address the dataset shift problem following the base assumptions of Transfer Learning, and different categorizations of these methods have been reported [72,73]. One of the first and most important review on Transfer Learning methods was proposed in [72]. However, several new strategies were proposed in the following years (e.g., Domain Generalization-based works).

Table 1
Datasets on emotion recognition classified according to the employed stimuli (*av* = "audiovisual", *a* = "audio"), #EEGchannels, #subjects, #sessions, #trials, trial duration, reference theory, and #classes.

Dataset	Stimuli	#EEG channels	#subjects	#sessions	#trials	Trial duration [s]	Reference theory	#classes
SEED	*av*	62	15	3	15	240	Dimensional	valence (1–3)
SEED IV	*av*	62	15	3	24	120	Discrete	happiness, sadness, fear, neutral (4)
DEAP	*av*	32	32	1	40	60	Dimensional	valence (1–9), arousal (1–9), dominance (1–9)
DREAMER	*av*	14	23	1	18	60	Dimensional	valence (1–5), arousal (1–5), dominance (1–5)
ASCERTAIN	*av*	1	58	1	36	60	Dimensional	valence (1–7), arousal (1–7)
MAHNOB	*av*	32	27	1	20	min 39.4 max 117	Discrete	disgust, amusement, joy, fear, sadness, neutral (6)
MPED	*av*	62	23	2	28	min 141 max 295	Discrete	joy, funny, anger, disgust, fear, sad, neutrality (7)
MDME	*a*	14	12	5	24	37	Dimensional	valence (1–2), arousal (1–2)
SDMN	*a*	32	26	1	16	30	Dimensional	valence (1–2), arousal (1–2)
CMEED	*av*	40	33	1	4	min 67 max 99	Discrete	amusement, fear, anger, tenderness (4)

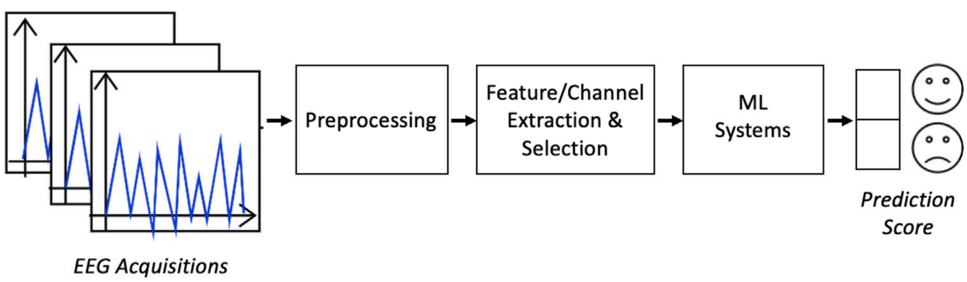

Fig. 2. A pipeline of a classical ML process involving EEG signals. After the data have been preprocessed and divided into epochs, suitable features are extracted together with a proper channel selection strategy (if available). Next, the obtained features are fed to the ML system. Feature extraction procedure can be embedded into the ML system block in the case of end-to-end deep learning methods (such as DNNs).

4. Papers selection method

The present literature review took into account the guidelines for systematic literature reviews presented by Kitchenham [74]. In addition, PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) recommendations were adopted in order to transparently report the document extraction process [24]. The survey was conducted covering the period between January 2010 to March 2022, using the following databases: *Scopus*, *IEEE (Institute of Electrical and Electronics Engineers)*, *Xplore*, and *PubMed*.

In accordance with the PRISMA recommendations, the review pipeline comprised four successive steps: 'Identification', 'Screening', 'Eligibility', and, finally, 'Inclusion', which considerably reduced the amount of surveyed work. For the initial identification of the articles, the following query was used in all the selected data sources, taking into account titles and abstracts: EEG AND (Emotion OR Preference) AND ("Domain Adaptation" OR "Domain Generalization" OR "Transfer Learning" OR "Adversarial" OR "Transfer" OR "Cross Session" OR "Cross Subject" OR "Cross Gender" OR "Non-stationary EEG" OR "Subject Invariant" OR "Subject Independent" OR "Cross Individual").

From the first phase, 637 articles were collected. Therefore, duplicated papers, not peer-reviewed, or not written in English were excluded from the review as an initial prescreening process. For each paper that passed the screening stage, a careful examination of the full text was carried out. In a final screening, further papers were excluded according to the following exclusion criteria: (a) generalizability issue not explicitly stated, (b) absence of a cross-subject/cross-session validation strategy, (c) adoption of a 'multimodal' approach (i.e. aimed at supporting EEG-based classification with other biosignals and/or information), (d) lack of focus on Emotion Recognition. As a result, 79 papers remained and were included in the review analysis. The complete flow diagram of the systematic review process according to PRISMA is presented in Fig. 3.

5. Results

The analyzed works can be divided into two main big families, according to the assumption on the origin of the handled data (e.g. from a single population/domain described by the same probability distribution or from different populations/domains):

- *Classical ML approaches*: all data are assumed to belong to the same population and are described by the same probability distribution;
- *Transfer Learning (TL) approaches*: these methods assume that data can belong to different populations (domains). Data with heterogeneous probability distributions can lead to the dataset shift problem, resulting in a loss of the model's generalization. In general, the main goal of a TL method is to reduce the discrepancy between the probability distributions of different domains, exploiting the knowledge acquired from one or several *source* domains to solve a problem in a *target* domain.

Notation

Except where otherwise specified, in the remaining of this survey the following notation will be used: F refers to a given *feature space* and L to a given *label space*. $\mathbf{x}^{(i)}$ refers to a generic data point belonging to F, and $y^{(i)}$ refers to a generic label from L. $\{\mathbf{x}^{(i)}\}_{i=1}^{m}$ is a set of m unlabeled data points where $\mathbf{x}^{(i)}$ belongs to F, while $\{(\mathbf{x}^{(i)}, y^{(i)})\}_{i=1}^{n}$ is

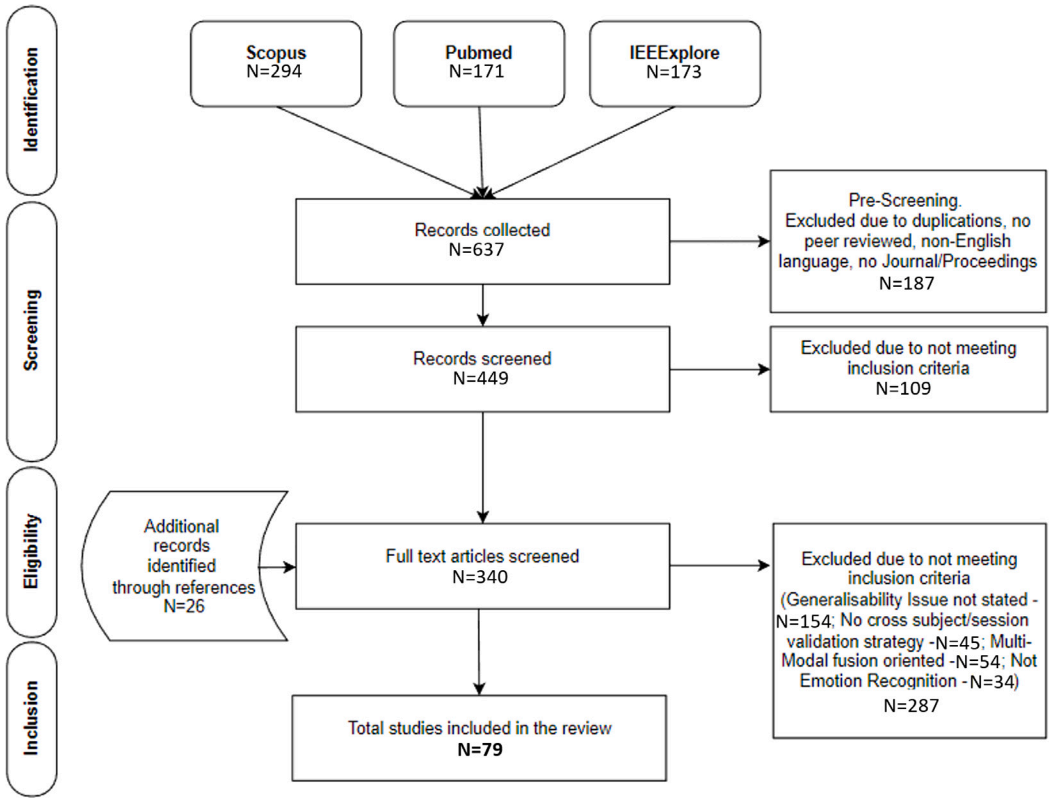

Fig. 3. PRISMA flow diagram of the systematic review process.

a set of n labeled data points, where $\mathbf{x}^{(i)}$ belongs to F and $y^{(i)} \in L$ is the corresponding label. A classifier C can be viewed as a functional mapping $C : \mathbf{x} \in F \to y = C(\mathbf{x}) \in L$ usually learned by the data. A *Task* T is a set composed by a label space and a classifier, i.e. $T = \{L, C\}$.

5.1. Classical ML approaches

A model trained on a set of EEG data acquired from a given subject at a specific time (or during a specific session) could not work as expected in classifying EEG signals acquired from different subjects or from the same subject at different times, resulting in poor generalization performance. To deal with this problem, several solutions based on ML approaches have been proposed over the years such as semisupervised and transductive methods. Semisupervised methods assume that a part of unlabeled data is available during the training stage, together with the labeled one. However, differently from TL methods, no assumptions about the data distribution are made. The idea is that further data, also if not labeled, can help the training procedure to better generalize. An example of semisupervised method applied to Emotion Recognition in the EEG domain is provided in [75]. The proposed Optimal Graph coupled Semi-Supervised Learning (OGSSL) model is able to learn a graph of similarity between input features assuming that, if two data are similar, they are probably acquired in the same affective state. Therefore, an optimization problem is addressed to project the data into a new space where this assumption is verified, allowing both to make predictions and to identify discriminative EEG features. Differently, [76] proposed semi-supervised Joint Sample and Feature importance Evaluation (sJSFE), a method exploiting both labeled and unlabeled data coming from different EEG acquisition sessions to characterize the importance of data sample. Differently from semisupervised methods, transductive methods [77] assume that *all* the unlabeled target data of the classification problem are available in the training stage. Furthermore, as in semisupervised but differently from domain adaptation methods, in transductive methods no assumption about the distribution of the data is made. The idea is that in several problems there is only a specific set of data to classify, and it is available at training time. Note that in standard ML approaches, the goal is to generalize on new unseen data and a labeled test set is used only to validate the learned model on new, unseen data adopting the inductive learning principle [77]. In transductive learning, the goal is to correctly classify only the available unlabeled set, therefore the classification problem is defined only on the available unlabeled data. For example, differently from classical SVMs that leverage only on labeled data, Transductive SVMs [78] exploit both labeled and unlabeled test data to find the best decision boundary between classes, using the unlabeled data as an additional set of information in the training stage. One of the main drawback of TSVM is that an estimation of the number of unlabeled data belonging to each class is needed. Progressive TSVM [79] tries to solve this problem by progressively labeling the unlabeled data during the training. In this review [80] is the only study that explicitly uses transductive methods in EEG Emotion Recognition, where a Progressive TSVM is used in a cross-session ER problem on EEG data. Instead, the greatest part of the reviewed proposals consisted in proper *feature transformation* and/or *feature selection* processes. The former wants to transform the data features to hold only the most useful information, assuming that it is shared between all the subjects/sessions, while the latter are methods to select only the most useful features from the input signals without changing them. Usually, in a classical ML pipeline, the feature extraction/selection is one of the first steps, where the data are transformed before being fed to the machine learning model. These methods assume that there is no prior knowledge of the actual data on which the model will be used post-training. This stems from a traditional ML assumption that all data, whether used in training or not, belong to the same probability distribution, implying that the training data should enough for the model to generalize effectively.

In the EEG Emotion Recognition context, this means that a proper EEG data transformation is enough to allow a ML model to generalize well on never seen EEG data, regardless of whether these new data belong to a subject/session used during the training or not. Going deeper, in a ML problem on EEG data the feature extraction and selection process can be made considering two different aspects of the signal: (i) the acquired EEG features or (ii) the electrodes composing the acquisition device. In the first case, a proper transformation or selection strategy for the EEG features is made, while in the second case the focus is on selecting the more representative electrodes for the task. In the following of this subsection, the remaining classical ML approaches are discussed considering these two different approaches.

EEG features extraction/selection strategies

The reviewed literature proposed several works inspecting if several known feature extraction methods are suitable to generalize across several ER settings [81,82]. In particular, in [81] the authors investigate the robustness of ER features in different experimental conditions, such as different subjects and datasets. The work conducted in [83] inspects if features encoded into event-related potentials allow to discriminate between emotions in a given subject and also if they can be adopted across different subjects. Differently, [84] explores the adoption of Factor Analysis [85] in EEG Emotion Recognition. In [86] the adoption of averaged features in cross-subject generalization is inspected. Instead, in [87] a new filter (Hybrid Adaptive Filter) to isolate emotion-related features is developed leveraging on both Empirical Mode Decomposition and genetic algorithms.

In [88,89] the classical Sequential Backward Selection (SBS) approach for feature selection is applied to find a set of features able to generalize across different subjects. To find the best subset of features, SBS decreases the number of features in an iterative way measuring, at each step, the performance on a given classifier (SVM in [88], Decision Trees in [89]). Similarly, [90] inspects Sequential Feature Selection (SFS), an exhaustive procedure over all possible features combinations with the aim to find the best one in terms of classification performance. In [91] a feature selection and a channel selection framework are adopted to mitigate the subject-to-subject variability.

In [92,93], a family of Transferable Recursive Feature Elimination (TRFE) methods is used to remove the EEG features resulting not enough generic across all subjects involved. The study is validated on DEAP dataset in both within-subject and cross-subject scenarios using SVM as classifier. In [94] Cross-subject Recursive Feature Elimination (C-RFE) is used to rank features by importance and remove the less important ones.

In [95], an enhanced version of the established Differential Entropy (DE) features is introduced. Unlike DE that focuses solely on the frequency domain, the proposed Dynamic Differential Entropy (DDE) features incorporate both the time and frequency domains of the data. The goal is to learn common characteristics across different subjects maximizing the difference between classes and minimizing, at the same time, the difference within classes. [96,97] inspect the behavior of Dynamic Entropy features in cross-subject EEG Emotion Recognition adopting SRU-based models [98] and SVMs as ML models respectively.

In [99], latent representations of the EEG data from SEED and DEAP datasets are learned through a Variational Auto Encoder (VAE, [100]) and then classified using a Long Short-Term Memory (LSTM). VAEs are generative neural networks able to learn embedding of data in a latent space. As a classical autoencoder, a VAE is composed of an encoder network able to project data to an embedding space, and a decoder network able to reconstruct the original input from the embedding. VAEs assume that all the data are generated by a random process involving latent variables. The ability of VAEs to represent latent EEG factors is also analyzed in [101], along with classical Auto-Encoders (AEs) and Restricted Boltzmann Machines (RBMs). The generalization performances are evaluated on DEAP and SEED dataset, exploiting an LSTM as emotion classifier.

In [102], the cross-subject problem is tackled using Variational Mode Decomposition (VMD) as feature extraction technique. Performance is measured adopting a Deep Neural Network (DNN) as an emotion classifier. Despite the encouraging results reported in a cross-subject approach, no reason seems to be given or discussed as to why the proposed system performs well in the cross-subject scenario. In [103–105] is shown that some normalization functions usually adopted to preprocess the EEG data can affect the cross-subject performance.

In particular, in [103] several normalization functions are applied and evaluated on the available data following two different schemes: (i) *All-subjects*, where the whole dataset was normalized regardless the subjects involved, (ii) *Single-subject*, where the normalization is applied individually to each subject. The All-subject one is the most common method to normalize the entire dataset. The authors show empirically on the SEED dataset that the Single-subject Z-score performs better in an EEG emotion recognition problem than other normalization schemes, such as min–max normalization. On the same data, in [104] the authors apply a single-subject Z-score normalization after each layer of a neural network (Stratified Normalization).

Differently, in [105] transforms the original features into binary vectors, where each component has 0 or 1 as value if the feature is lower or higher than the median feature value, respectively. The basic assumption is that this transformation leads to a more effective reduction of the subject-dependent component of the EEG signal.

Channel-based strategies

To achieve EEG-based cross-session ER, in [106,107], a general set of channels valid across the subjects is searched exploring several channels selection strategies. Instead, the authors of [108] learn the importance of each EEG channel in an ER task to retain discriminative features discarding the noisy and redundant ones.

The authors of [109] propose a neural network model that includes a channel-attention layer designed to select the most important channels for identifying a set of emotions. Notably, the different subjects' personalities are taken into account, training a different network for each group of subjects with similar personalities. Validation is made on the ASCERTAIN dataset. This dataset results particularly suited for this task, since it links together personality, emotional state and physiological reactions. The placement of the electrodes is taken into account and modeled as a graph.

Graph representation methodologies resulted effective in modeling structured data, achieving significant performance in several applications such as EEG emotion signal processing [110]. In particular, Graph Neural Networks (GNNs, [111]) are useful to retain the spatial structure of the electrodes disposition. Usually, the spatial disposition of the electrodes on the scalp is represented by a fixed and given a priori graph structure. Differently, Dynamical Graph CNNs (DGCNNs, [110]) and Self-Organized Graph Neural Network (SOGNN, [112]) change the graph structure leveraging on the input brain signals. The resulting graph can be processed by graph convolutional layers to extract the more suitable features and channel for ER tasks.

5.2. TL methods

With respect to Classical ML, TL approaches are gaining popularity thanks to their better performance reported in recent studies. In literature, current TL methods are divided into two main categories according to the availability of data belonging to the target distribution during the training phase:

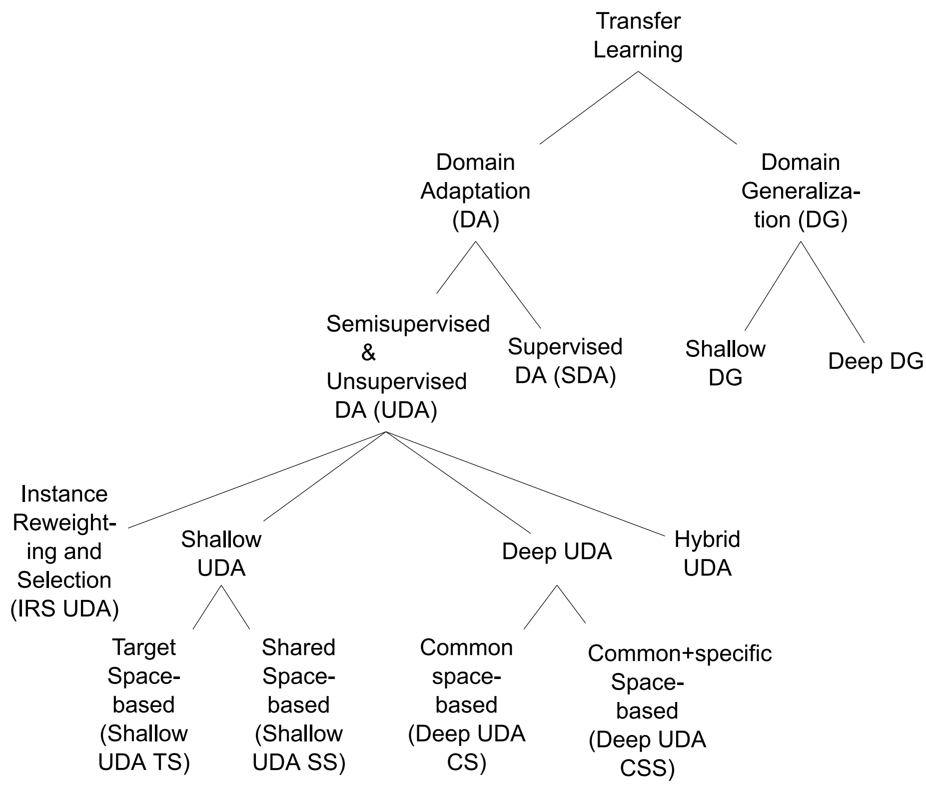

Fig. 4. The proposed taxonomy of the TL methods in EEG-based ER. Starting from the root node, the criterion "target data used in the training phase" leads to the creation of two child nodes: Domain Adaptation (if yes) and Domain Generalization (if no). Domain Generalization in turn generates two nodes depending on the type of data transformation: learned (Deep DG) or unlearned (Shallow DG). From Domain Adaptation, the Supervised DA (SDA) node is generated if all target data labels are used in the training phase; otherwise, the Semisupervised/Unsupervised DA (UDA) node is generated. From the latter node, four branches distinguish the data handling strategy: (i) data is transformed using an a priori defined function (Shallow UDA), (ii) the data transformation function is learned as part of the method (Deep UDA), (iii) data is selected or reweighted using some strategy (Instance Reweighting and Selection - IRS UDA), and (iv) a combination of the previous approaches is applied (Hybrid UDA). The Shallow UDA methods are divided into two leaf nodes according to the projection space of the transformation: (i) all data is projected into the same space as the Target domain (Target Space-based - Shallow UDA TS), (ii) a new shared space is used between the Source and Target (Shared Space-based - Shallow USA SS). Similarly, for Deep UDA methods, two branches lead to two leaf nodes: (i) Common Space-based (Deep UDA CS) if the Source and Target are projected into a new shared space, (ii) Common+Specific Space-based (Deep UDA CSS) if Source and Destination are first projected into a single shared space, then, for each available domain, a projection is used in an ad hoc space.

- *Domain Adaptation (DA) methods*: the DA general assumption is that data of the target domain are available during the training of the model, together with data belonging to the source domain(s). For instance, in the EEG Emotion Recognition, data acquired from both source and target subjects/sessions are available during the model training.
- *Domain Generalization (DG) methods*: in these methods, data belonging to several domains different from the target domain are available and can be used during the training, but no data from the target domain are available at this stage. The knowledge extracted from multiple source domains is exploited to improve the model generalization. For instance, in the EEG Emotion Recognition, labeled data acquired from different subjects/sessions can be considered as belonging to different domains, and can be used to build a model able to generalize to a new unseen subject/session, where no data is available during the construction of model. Domain Generalization methods can be further split into two subcategories depending on the type of data transformation: learned (*Deep DG*) or unlearned (*Shallow DG*).

Regarding the DA methods, a further division can be made considering how the available target data labels are used in the training phase. In particular, we can identify the following cases:

- *Supervised DA (SDA)* methods: these methods benefit from the availability of labeled data from the target subject/session during the training stage; typical examples of Supervised DA methods rely on pretrained models, where a model already trained on a known source domain is adapted to work in a new target domain exploiting the available target labeled dataset, or studies relying on few-shot learning, based on ML model built using a small amount of labeled data available from the target space.
- *Unsupervised and Semisupervised DA (UDA)* methods: these methods benefit from unlabeled data coming from the target subject/session available during the training stage. The method is *Unsupervised* if only unlabeled target data are exploited, *Semisupervised* if further labeled target data are also available.

UDA methods, in turn, can be distinguished based on the strategy adopted for handling data:

- *Shallow UDA*: data are transformed using a function defined *a priori*;
- *Deep UDA*: a data transformation function is learned as part of the method in a end-to-end manner;
- *Instance Reweighting and Selection (IRS UDA)*: data are selected or reweighted using some strategies;
- *Hybrid UDA*: a combination of the previous approaches is applied.

Shallow UDA methods can be further divided according to the projection space of data transformation: (i) all the available data are projected into the same space of the target domain (Target Space-based - *Shallow UDA TS*), (ii) a new shared space is built for both source and target (Shared Space-based - *Shallow UDA SS*). Similarly, two subcategories can be identified also for Deep UDA methods: (i) Common Space-based *(Deep UDA CS)* if the source and target are projected into a new shared space, (ii) Common+Specific Space-based *(Deep UDA CSS)* if source and

Destination are first projected into a single shared space, then, for each available domain, a new projection is used to map the data in an ad hoc space. Relying on the above considerations, a taxonomy of the TL methods used in EEG-based Emotion Recognition is reported in Fig. 4.

In general, Transfer Learning methods are based on the concept of domain. Following the survey of Pan et al. [72] and the notation introduced in , a domain can be defined as a set $D = \{F, P(X)\}$ where F is a feature space and $P(X)$ is the marginal probability distribution of a specific dataset $X \in F$.

Transfer Learning wants to exploit the knowledge of a domain D_A on a task T_A to resolve the same or another task T_B on another domain D_B. By the definition of domain, it is straightforward that two domains $D_A = \{F_A, P(X_A)\}$ and $D_B = \{F_B, P(X_B)\}$ can be considered different if they differ in the feature spaces or in the marginal probability distributions. Obviously, the same holds for two Tasks $T_A = \{L_A, f_A\}$ and $T_B = \{L_B, f_B\}$. More in details, the following cases can happen:

1. $D_A = D_B$ and $T_A = T_B$: since the Tasks and the domains are the same, this can be considered a standard ML Problem.
2. $D_A \neq D_B$: $F_A \neq F_B$ or $F_A = F_B$ and $P(X_A) \neq P(X_B)$
3. $T_A \neq T_B$: $L_A \neq L_B$ or $f_A \neq f_B$.

Due to the non-stationarity of the EEG signals between different subjects/sessions, an emotion classification problem can be viewed as a multi-domain problem where the data belonging to each subject/session are sampled from different domains. More specifically, in an emotion classification problem we can assume that two different subjects/sessions A and B share the same feature space (i.e. the EEG data representation) and the conditional data distributions $P(L_A|X_A) = P(L_B|X_B)$ are the same, but the marginal probability distributions are different on the available data, i.e. $P(X_A) \neq P(X_B)$. Therefore, generalizing across different subjects/sessions can be viewed as reducing the discrepancy between several domains according to some measurements.

In the current literature, TL strategies can be divided into DA and DG families. These families differ mainly in which data are processed during the learning stage. DA methods assume that data sampled from at least two different domains are available, consisting in one or more source domains and one target domain. Usually, methods involving more that a single source domain are said *multi-source*. In the Emotion Recognition field, the proposed tasks usually involve several subjects or sessions with different statistical properties, therefore they can be easily reduced to TL framework. In particular, since data belonging to different subjects/sessions can have different statistical properties due to the non-stationarity of the signal, each subject/session can be viewed as a different domain. However, several TL strategies proposed in literature assume only one source and a target domain, the former corresponding to *all* the available labeled data (usually the whole training set), and the latter corresponding to the unlabeled one (usually the test set). In other words, all the labeled data available are considered as belonging to the same domain, regardless the actual probability distributions they belong to. Therefore, these methods implicitly assume that all subjects/sessions belong to the same probability distribution, which is equivalent to considering all data as belonging to the same subject/session. Instead, more recent works handle the available data in a multi-source framework, considering each labeled subject/session as belonging to different domains.

In contrast, DG methods assume that labeled data sampled from $d \geq 2$ source domains are available, while no data from the target domain is known. DA and DG methods are getting attention in the scientific literature in different contexts (e.g. image classification and voice recognition), and several proposals have been made until now. One trend of the literature is to adapt DA/DG methods originally proposed for a context to another one. Recently, several attempts were made to adapt well-established DA/DG methods in tasks involving the EEG-based Emotion Recognition. For example, in [113] DA strategies initially proposed for image classification are adapted for EEG Emotion Recognition. However, each context has its characteristics and peculiarities, making the transfer of a DA method from a task to another not straightforward.

UDA methods

When unlabeled data belonging to the target domain are used during the training stage, the method is considered UDA. If no labeled target data is available in the training stage, the approach is said Unsupervised. Conversely, if labeled target data is also exploited during training, the method is considered Semisupervised. Several UDA methods relied on minimizing discrepancy measures between the source and the target domains. In [73], these methods are categorized into *shallow UDA* and *deep UDA*, where:

(A) *Shallow UDA*: a function to build a new data representation is given *a priori*, at most learning the mapping parameters.
(B) *Deep UDA*: the data representation is fully learned as part of the UDA strategy.

However, this categorization does not consider works assuming that not all the training data can effectively be useful for the target space. In order to avoid negative transfer [114], a selection of the training data may be necessary. Therefore, in this work the *Instance Reweighting and Selection (IRS UDA)* category is added. Reviewing the literature, it results that IRS UDA are often used together with Shallow UDA and Deep UDA. In the proposed taxonomy, such methods are identified as *Hybrid UDA*.

In the following part of this Section, reviewed studies are reported according to the categorization above discussed.

(A) Shallow UDA methods

Shallow UDA strategies proposed in literature typically rely on one of following alternatives:

(A1) *Target Space-Based (Shallow UDA TS)*: these methods search for a good transformation which directly maps data belonging to the source domain S to the target domain T space;
(A2) *Shared Space-Based (Shallow UDA SS)*: these methods aim to find a transformation that maps source S and target T data in a new shared space where the discrepancy between S and T is minimized.

Once all the data are projected in a common space, any supervised method can be applied for classification, as both source and target domains follow a similar distribution.

(A1) Shallow UDA TS methods:

The proposal made in [115] tried to align the source space toward the target one (Subspace Alignment, SA). Rather than using the available data in the original feature spaces, Principal Component Analysis (PCA) is adopted for a more robust and compact data representation. More specifically, two PCA projection matrices Z_S and Z_T are computed for the source and the target domains, respectively. Therefore, a transformation matrix M^* able to align the source space to the target one is computed as:

$$M^* = \arg\min_M ||Z_S M - Z_T||_F^2.$$

This problem has a closed form solution, that is $M^* = Z_S^T Z_T$.

In [116], Adaptive Subspace Feature Matching (ASFM) is proposed for EEG-based Emotion Recognition. Based on SA, ASFM takes into account that the subject's fatigue and attention level can lead to mismatched marginal and conditional distributions. In [117] (Multi-Subject Subspace Alignment, MSSA) the ASFM strategy is applied considering each source subject individually (multi-source), using the projected data as input for subject-specific classifiers.

Differently, [33] adopted Robust Principal Component Analysis (RCA, [118]). RCA decomposes a set X of data as $X = L^* + S^*$, with L^*

and S^* low-rank matrix and sparse matrix respectively. These matrices are computed resolving the following optimization problem:

$$L^*, S^* = \arg\min_{L,S} ||L||_* + \lambda||S||_1 \text{ s.t. } X = L + S$$

where $||\cdot||_*$ is the matrix nuclear norm, $||\cdot||_1$ the l_1 norm and λ a weighting parameter.

In [119], Style Transfer Mapping (STM, [120]), a method originally proposed for personalized handwriting recognition task, is adapted for EEG Emotion Recognition to generalize across different subjects. In a nutshell, STM maps the source data to the target data by means of an affine transformation. The solution of the proposed problem has a closed form, so it can be easily computed. Few labeled target data are used to select source data, therefore the method assumes that a small amount of labeled target data is available.

(A2) Shallow UDA SS methods:

Among the Shallow UDA SS methods, the Maximum Mean Discrepancy (MMD, [121]) is one of the most used discrepancy measure in DA/DG strategies. MMD was originally proposed to test if two probability distributions are different or not. Formally, the authors show that, in a Reduced Kernel Hilbert Space (RKHS), a discrepancy measure between two distributions p and q can be defined as:

$$MMD(p,q) = ||\mathbb{E}_{X_S \sim p}(\phi(X_S)) - \mathbb{E}_{X_T \sim q}(\phi(X_T))||_H^2$$

where $\phi(\cdot)$ is an appropriate feature mapping. It results that, in a RKHS, $MMD(p,q) = 0$ if and only if p and q are the same.

MMD can be empirical estimated as the difference between the averages of two datasets sampled from the two distributions, once they are projected in a RKHS. Therefore, considering X_S and X_T sets sampled from the source and the target domain respectively, empirical $\widehat{MMD}(X_S, X_T)$ can be expressed as:

$$\widehat{MMD}(X_S, X_T) = \left\| \frac{1}{|X_S|} \sum_{i=1}^{|X_S|} \phi(\mathbf{x}_S^{(i)}) - \frac{1}{|X_T|} \sum_{i=1}^{|X_T|} \phi(\mathbf{x}_T^{(i)}) \right\|_H^2$$

where $\mathbf{x}_S^{(i)}$ and $\mathbf{x}_T^{(i)}$ are elements of X_S and X_T, respectively.

Transfer Component Analysis (TCA, [122]) is one of the most well-known MMD-based DA method. Two different TCA versions were originally proposed: (i) an unsupervised one, consisting in finding a data transformation such that the data variance is maximally preserved and the MMD distance between the domains' distributions is minimized, and (ii) a *supervised* one, where the dependence between training data and labels is taken into account.

A performance evaluation of the Unsupervised TCA applied on EEG data for Emotion Recognition was made in [123]. Instead of using all the available EEG data to build the transformation function, a random selection of samples from source domain data is considered, leaving out the data of a subject as target. In [124], several TCA spaces with different dimensions are evaluated on the SEED dataset. Instead, in [32] TCA is tested on self-made EEG data.

In [125] through Transfer Sparse Coding (TSC) the MMD was used to find a sparse representation of image data sampled from different distributions. Sparse representations are well-known data approximations obtained as linear combinations of elements in a set of basis functions. In a nutshell, a sparse coding method searches for a representative over-complete set of basis functions (a *dictionary*) together with an encoding that best represents the data. In its simplest form, the sparse coding problem can be expressed as

$$B^*, S^* = \arg\min_{B,S} ||X - BS||_F^2 + \lambda \sum_{i=1}^{n} |\mathbf{s}^{(i)}|$$

where $X \in \mathbb{R}^{m\times n}$ is a matrix containing the n data points to approximate while $B \in \mathbb{R}^{m\times k}$ and $S \in \mathbb{R}^{k\times n}$ are the dictionary matrix and the encoding matrix respectively, with $k > m$ to ensure the over-completeness. The sparsity is induced by the second equation term on the coefficient matrix columns $\mathbf{s_i}$ and regularized through the hyperparameter $\lambda \in \mathbb{R}$. However, if X is composed of data sampled from two different domains (e.g., $X = [X_S|X_T]$) the above formalization does not take into account the differences between the marginal distributions. To deal with this problem, [125] adds to the objective function a further regularization term that considers the MMD distance between the different domains of the input data.

Similarly, PCA and Fisher criteria [126] are used together in [127] with the aim to compute a common dictionary between source and target domains, but preserving both the local information between samples and the discriminative knowledge between the domains. The proposed strategy requires a little set of labeled data from the target domain during the training stage, resulting a Semi-supervised DA approach.

While it is not specifically designed for Domain Adaptation, Kernel-PCA (KPCA, [128]) is often used in comparisons with several studies involving DA methods. In fact, KPCA uses the kernel trick [129] to project the data into a kernel space. Projected data are then fed to PCA. A comparison between Kernel-PCA and TCA for EEG Emotion Recognition is reported in [123].

In [130] several shallow UDA approaches such as TCA, KPCA, TSVM are evaluated on SEED dataset, while in [131] similar methods are evaluated on SEED and DEAP also for cross-dataset generalization.

Subspace Alignment Auto-Encoder (SAAE) [132] is a different proposal which combines together auto-encoders and subspace alignment. The subspace alignment is obtained through MMD and KPCA to maximize the embedded data variance. Before the transformation, an auto-encoder trained on both source and target data was employed to extract features from the data. One criticism of MMD and similar approaches is that they aim to minimize the discrepancy between distributions only by relying on input features, without considering class predictions. In [133] the class predictions are exploited to reduce the *class confusion* issue, occurring when a classifier trained on data belonging to a source domain may confuse to distinguish the correct class from a similar class in the new domain. Th proposed Minimum Class Confusion (MCC) loss exploits the prediction on the target data to reduce class confusion. MCC is defined as

$$MCC\big(C(X_T)\big) = \frac{1}{|L|} \sum_{i=1}^{|L|} \sum_{j=1}^{|L|} |Q_{ij}|$$

where Q is the class correlation matrix. More in detail, each entry Q_{ij} reveals the relationship between the class $i \in L$ and the class $j \in L$ in a given batch of data X_T. A possible way to compute Q is reported in [133]. [134] adopts Gated Recurrent Unit (GRU, [135]) together with MCC loss in an ER task.

The authors of [131] exploit Maximum Independence Domain Adaptation (MIDA) [136] in the EEG Emotion Recognition case. MIDA projects the data into a subspace to reduce the inter-domain discrepancy in distributions considering independence between domains through the Hilbert–Schmidt Independence Criterion (HSIC, [137]).

(B) Deep UDA methods

In deep UDA approaches, a transformation of the feature data representation is embedded into the DA method, in an end-to-end way.

Deep UDA methods can be further divided in:

- (B1) *Common Space (Deep UDA CS)*: source and target are projected in a new shared space;
- (B2) *Common+Specific Spaces (Deep UDA CSS)*: source and target are first projected in a unique shared space, then, for each available domain, a projection into an ad-hoc space is adopted.

(B1) Deep UDA CS methods:

Common Space methods assume that data belonging to both source and target domains can be projected in a shared common space where the classes are more easily separable. As Deep UDA CS methods, [138] (Deep Domain Confusion, DDC) consists in two identical neural networks trained together, the former classifying data from the source domain, the latter adapting the distance between source and target domains using features of target data. In [139], an extension of MDD able to exploit the hidden layers activations of a CNN was proposed. The suggested Joint Maximum Mean Discrepancy (JMMD) uses the activations provided by all the CNN layers as surrogates of the $P(X_s, Y_s)$ and $P(X_t, Y_t)$ distributions. It then computes a generalization of the MMD metric on joint distributions to measure discrepancy. The JMMD has been investigated in [140] as part of the loss function for a DNN in an Emotion Recognition task. Instead, the authors of [141] used DDC with Residual CNNs [142] for cross-subject EEG Emotion Recognition. To be fed to CNNs, the EEG inputs are firstly transformed into Electrode-Frequency Distribution Maps (EFDMs, [143]).

The authors of [144] proposed a DA framework exploiting a standard CNN, usually composed by a sequence of convolutional layers ended by a fully-connected ones. The starting assumption is that in a DNN the transition from general to particular task features grows with the increasing of the network depth. Indeed, in a CNN, while the initial convolutional layers learn general features, the final fully-connected ones learn domain specific features that are not transferable. Their proposed model (Deep Adaptation Network, DAN) deeply adapt the final fully connected layers minimizing the Multi-Kernel Maximum Mean Discrepancies (MK-MMD, [145,146]), a multiple kernel variant of MMD used as distribution discrepancy measurement. DAN was evaluated in EEG Emotion Recognition on SEED and SEED-IV in [147].

In [148] the proposed Multi-Spatial Domain Adaptation Network (MSDAN) aligns source and target domains considering the spatial relationships between the electrodes. This is done by using Graph Convolutional Layers and exploiting MMD distance in the resulting graph space. Differently from other works, [148] uses data acquired in a Virtual Reality (VR) environment to generate stimuli, and the cross-device problem is taken into account.

One of the most used deep UDA strategies is the Domain Adversarial Learning, proposed in [73,149,150]. The basic idea is to make the data distributions indistinguishable for an ad-hoc domain classifier. The authors proposed an embedded DA problem formulation joining together the desired task and the source–target discrepancy.

This can be obtained by a DNN model (Domain Adversarial Neural Network, DANN) that, for each input, predicts both the corresponding class and the belonging domain. DANN is composed of three main components: a feature extractor, a label predictor, and a domain classifier. The role of the domain classifier is to distinguish between source and target domain samples, while the feature extractor is responsible for transforming the input data into a feature representation that should be domain-invariant, therefore minimizing the domain-specific information. Finally, the label predictor is typically used for the main classification task. The learning stage searches for a mapping maximizing the class prediction performances and, at the same time, also maximizing the domain classifier loss to make the feature distributions as similar as possible. In [151] a general framework for adversarial unsupervised adaptation methods is proposed.

DANN is evaluated in EEG Emotion Recognition task in [152] on SEED. In [153] BiDANN, a variation of the original DANN, is adopted for EEG Emotion Recognition, but considering the differences between the brain hemispheres. More in detail, EEG data from the two hemispheres are processed separately: two different feature mappings, together with a domain discriminator, are learned for the brain hemispheres. The differences between the hemispheres in DA are not addressed only by BiDANN; for instance, BiHDM [154,155] uses two different RNN to encode the data belonging to the two hemispheres, while a domain discriminator is used to mix up the features of the source and the target domains. [156] a bidirectional LSTM (BiLSTM) is used to capture regional and global spatial–temporal features relying on information provided by the channel placement. In particular, features are grouped into several clusters corresponding to different brain regions determined by the spatial locations of EEG electrodes. In this way, BiLSTM networks should learn regional deep features, further weighted by a proper dynamic weighting scheme. A final domain classifier is adopted to enforce the learned space to be discriminative between different domains (in this case, subjects).

In [157] the authors propose a new DA method which is framed in the context of deep adversarial learning approaches. In particular, a temporal convolutional network is used as encoder. The method is successfully evaluated in both cross-subject and cross-dataset. In [158, 159], domain adversarial approaches are used together with Graph Neural Networks (GNN, [113]) as feature extractor. In particular, the authors of [158] lead the learning process to focus on the more tricky areas of the feature space leveraging on an attention mechanism [160]. Performance is evaluated on SEED dataset. Instead, [159] proposed a Node-wise Domain Adversarial Training (NodeDAT) method to regularize the learning of a GNN for better subject-independent performance. In EEG literature, domain adversarial learning and attentional mechanisms are widely used in several other studies for EEG tasks, for example in [151,156,161–163]. In particular, in [156] possible differences between several brain regions are exploited with a proper attention module. In [164] (ATtention-based LSTM with Domain Discriminator, ATDD-LSTM) a domain discriminator in terms of LSTMs is presented to reduce the discrepancy between the distributions. An attention-based encoder–decoder focuses on emotion-related input data, helping the final classification probability estimation. The authors of [165] exploits the Covariance Matrices between EEG data and Riemannian distances [166]. The work proposed a new kind of ANN (daSPDnet) able to retain the intrinsic geometry information of the data. However, a little set of labeled data belonging to the target domain are required during the training process, resulting as a semi-supervised method. A similar approach, also requiring a few of labeled target data, was proposed in [167].

In [151], Adversarial Discriminative Domain Adaptation (ADDA), a strategy to tackle the DA on an image classification task, was proposed. Differently from DANN, the ADDA basic idea consists in building two different functions for the source and the target domains, represented with two different encoders E_S and E_T, respectively. E_S is trained together with a classifier C using labeled data from the source domain. Then, through an adversarial learning procedure, E_T is trained to map the target domain data in the same output space of E_S. Consequently, target data can now be classified by C. A similar idea was adapted for EEG Emotion Recognition tasks in [168] (Wasserstein GAN Domain Adaptation, WGANDA). More in detail, two generators, the former for the source and the latter for the target domain, are pre-trained to output two feature vectors of the same size. These vectors are assumed to belong to the same feature space. Next, an adversarial training phase based on Wasserstein distance minimization fine-tunes the parameters of the generators so that the outputs match each other as closely as possible. The combined outputs are then used as input to a final classifier.

Inspired by the MMD optimization made in [132], in [161], TDANN, a two stage DA method is proposed. In the first stage, MMD is minimized training a 2D CNN equipped with adaBN [169]. To be fed to the adopted 2D CNN and to preserve spatial information, the EEG input signals are transformed into images [170,171]. In the second stage, a domain discriminator is used to further reduce the distance between the source and the target distributions. Similarly, [172] proposed the Maximizing Domain Discrepancy for EEG-based ER (MMD-ER) architecture, which adopts both MMD and an adversarial training procedure to align the features produced by a CNN and an autoencoder, respectively. The proposal was tested in a cross-session task.

However, one of the main problems with DANN and similar networks is that only feature data without any labels are considered during the adversarial learning process. This type of DA methods can result in overlapping distributions of source and target domains by reducing the distance between them without considering the belonging classes. This overlap can lead resulting domains to not be distinguishable. Differently, in [173] (Maximum Classifier Discrepancy, MCD), the labels of the source domain data are also exploited to build good task-specific decision boundaries between the classes. In particular, MCD exploits different classifiers fed with the same inputs and evaluating the discrepancy. More in detail, two classifiers C_1 and C_2 having the same structure are fed with the output of a feature generator G. G can be fed with data $\mathbf{x}$ coming from the source or the target domain. The output of C_1 and C_2 are the labels of the input $\mathbf{x}$ transformed by G. Before the training step, C_1 and C_2 start from different initial states, rising two different classifiers after the training. How much the two classifiers disagree on their predictions on the same input is defined *discrepancy* by the authors. Indeed, the generator G is trained to minimize the discrepancy projecting source and target data in a same space, while C_1 and C_2 are trained to maximize the discrepancy (so that the two classification boundaries are far from each other). The learned generator G will be able to relocate the target domain data in the source space, but considering its most probable belonging class. Task-Specific Domain Adversarial Neural Network (T-DANN, [174]) is an MCD similar model proposed for EEG Emotion Recognition. T-DANN adapts the conditional distribution between domains and, at the same time, adapts classification boundaries between classes exploiting MCD in conjunction with a domain discriminator.

In [175] the authors propose an UDA approach for EEG-based Emotion Recognition based on a Multi-source co-Adaptation framework by mining diverse Correlation Information (MACI). Notably, MACI considers each subject as belonging to a different domain. The proposed method is compared with several standard (shallow) DA approaches and CNN-based (deep) DA approaches. Cross-subjects and cross-datasets evaluations are performed.

In [176], Neighborhood Component Analysis (NCA, [177]) is employed to learn the Mahalanobis distance between data. Therefore, data are linearly projected into a subspace such that the classification accuracy is maximized and the dimensionality of the EEG features is reduced. The obtained features are then used with Geodesic flow kernel for Unsupervised Domain Adaptation [178]. Instead, Multi-source Domain Transfer Discriminative Dictionary Learning modeling (MDTDDL) [179] adopts a dictionary learning procedure to learn a joint subspace between source and target domains [180]. DEAP and SEED are evaluated both in cross-subject and cross-session mode.

(B2) Deep UDA css methods:

Although several studies assume that a single common feature space is enough for DA, *Common+Specific Space (Deep UDA CSS)* methods go in different direction, assuming that a single shared classifier built in a shared space still has poor performance with never seen sessions/subjects. Notably, in these studies each available subject/session is considered as a single domain, and not as a whole.

Hypothetically, EEG data representations can be split into emotional components shared among all the subjects, and private components, specific to each subject. Leveraging on this hypothesis, [23] built a shared encoder and private encoders for each source subject data, with the aim to capture the subject-invariant emotional representations and private components, respectively. The learned encoders are then used to build several emotion classifiers. Finally, a classifier for a new subject is built. The parameters of these classifiers are learned exploiting the shared encoder. A fusion strategy between the classifiers' outputs is then applied to obtain the final classification result. However, the proposed framework requires few labeled target data, falling in the semi-supervised DA category. Multi-source EEG-based Emotion Recognition Network (MEERNet) [181] proposed a different classifier for each different domain (subject or session), preceded by a feature extractor shared by all the domains. Final classification is made averaging between domain-specific classifiers. Similarly, [182] proposed a framework composed of a common feature extractor to map all the domains in a common subspace, a main task classifier or regressor, and private discriminators for each domain. The training is made reducing the Wasserstein distance between the marginal distribution of each source domain and the target one in an adversarial way. In [183] the authors proposed a Multi Source-Marginal Distribution Adaptation (MS-MDA) algorithm for EEG Emotion Recognition. Also in this case, the key idea is that the final response is obtained by aggregating the responses of different target–source specific classifiers, preceded by a common feature extractor. Notably, the authors explore the impact of different types of data normalization on the performance of the proposed model. MS-MDA is also compared with several standard DA methods. Similarly, the authors of [184] proposed Multi-Source and Multi-Representation Adaptation (MSMRA), an approach with many similarities with MS-MDA. Both cross-subjects and cross-sessions evaluations are performed.

SDA methods

Supervised DA methods exploit labeled data from both source and target domain. In [41] a pretrained version of InceptionResnetV2 [185] is used as feature extractor for EEG data. The classification is made by a final network layer added to the InceptionResnetV2 network. Instead, [186] exploited DenseNet121 [187] as pre-trained model to build a new architecture fed with EEG data transformed into spectrogram images.

In [143] a CNN trained on different subjects and sessions of the SEED dataset is then fine-tuned on a small amount of data acquired from a subject belonging to DEAP dataset. This was made to evaluate the cross-dataset Emotion Recognition performance.

In [188] several classifiers trained on data belonging to different subjects and sessions are ensembled together in a final classifier suitable both for cross-session and cross-subject EEG Emotion Recognition. Differently, [189] adopted the few-shot learning paradigm for the Emotion Recognition task both in cross-subject and cross-session modalities. Few-shot learning assumes that few labels from different domains are available. The authors considered different subjects as different domains, therefore they used few labeled EEG acquisition for each subject to build a cross-subject emotion classifier. However, the adopted few-shot evaluation is hard to compare with classical ML evaluation protocols adopted in the greatest part of EEG Emotion Recognition literature. Other cases of few-shot learning in EEG Emotion Recognition are proposed in [190–192]. In particular, [191] exploits a few-shot learning approach together with an attention mechanism to deal with the excessive alignment problem. Few-shot learning-based approaches are also used in [192] where Siamese Networks [193] are used to evaluate the similarity between samples belonging to different domains. Siamese networks were originally proposed to determine whether two different inputs belong to the same class or not. In [192] the Siamese framework is enhanced to handle different domains.

IRS UDA & Hybrid UDA

IRS UDA methods take into account that not all the training data can effectively be useful for the target space. Indeed, a part of the data can lead toward bad performance, therefore it can be better to remove them or to reduce their weights in the training stage. In [194] TrAdaBoost [195], a semi-supervised DA method acting on the instances' weights, is used to score the source EEG data in order to avoid possible negative influence of the data during the training process. In a nutshell, a small amount of labeled target data available during the training stage helps to vote on the usefulness of each of the available source data instance. As initial step, only data belonging to the source subjects closest to the target one are selected. Similarity between subjects is computed according to the MMD similarity and fed to TrAdaBoost as auxiliary data. The authors of [196] propose Progressive Low-Rank Subspace Alignment (PLRSA), a novel approach based on TrAdaBoost algorithm and TCA. Importantly, a tiny amount of labeled target data is used.

The proposed method is evaluated in both cross-subjects and cross-sessions scenarios and compared with five state-of-the-art DA methods. The results seem promising, however the time complexity is a little more expensive than related state-of-the-art methods. In the revised literature, IRS UDA methods are often used as an initial step of other DA methods. For instance, in [34,197] the similarity between source and target EEG data is measured using the Pearson Correlation Coefficient and the Average Frechet Distance, respectively. In particular, in [197] EEG source data closer to the available target data are projected into a new space through TCA, together with the target one. Finally, the classification step is made by an Echo State Network (ESN, [198]).

In [199] (DMATN) source data belonging to the existing subjects are divided into several subdomains. Then, a set of subdomains is chosen as the most relevant ones for the target data. The proposed architecture combines together DAN and DANN to learn representation that are domains invariant.

DG methods

Differently from classical DA, DG assumes that labeled data from several domains are available, but no data from the target domain is observed during the training stage [200]. DG methods can be divided as:

(A) *shallow DG*: a data transformation is given *a priori*;
(B) *deep DG*: the data representation is learned as part of the DG strategy.

(A) Shallow DG methods

Shallow DG methods share the same principles of shallow UDA ones, building a shared space between domains, letting the input data representation unchanged. Domain Invariant Component Analysis (DICA) [200] searches for common features across several domains. Features are transformed by a learned orthogonal transformation able to minimize the dissimilarity between a set of known domains and, at the same time, preserving the relations between data features and their real labels. The authors also provided an unsupervised DICA version which did not take care of the class labels.

In [201], Scatter Component Analysis (SCA) is proposed. The authors' goal is to propose a method that fits both DG and DA requirements. SCA searches for a data transformation where, at the same time, (i) the source and the target domains are similar, (ii) elements of the same class are similar, (iii) elements of different classes are well separated, and (iv) the variance of the whole data is maximized. This is made introducing *Scatter*, a measure closely related to MMD. In [202], SCA and DICA are applied and evaluated on SEED dataset.

(B) Deep DG methods

On the other side, *deep DG* methods embed the data representation as part of the generalization strategy. In [203], data from similar subjects are used to train the same classifier. The similarity is computed through a clustering algorithm. This subset of similar subjects is used to train a final CNN classifier. Notably, in [204] a similar strategy is adopted also in the DA context.

[205] joined together BiDANN and VAE, obtaining a subject-invariant Bi-lateral Variational Domain Adversarial Neural Network (BiV-DANN). In the proposed work, the learned features are further refined by domain adversarial training made across different subjects, with the aim to learn subject-independent features. Furthermore, to maximize cross-dataset performance, spectral topography data of the EEG signal are used as input. The authors of [206] proposed a Multi-Branch Network (MBN) model to separate "background" from "task" features. In particular, two different branch networks learned background features and task features, respectively. The learning process adopted data with opposite task labels and a contrastive loss function.

6. Discussion

The pie charts in Fig. 5 show some statistics about the papers included in the survey. First of all, in Fig. 5. (a) is evident that almost three quarters of the studies surveyed (73.7%) focus on a cross-subject mode of generalization, while cross-session studies account for only 16.5% and only 9.8% operate a cross-dataset mode of generalization.

The pie chart in Fig. 5. (b) shows the number of times each EEG dataset is exploited in the reviewed literature. The mainly used datasets are SEED (44.6%) and DEAP (27.3%). This is followed by 9.9% of studies that propose their own self-produced dataset. Among the other datasets available in the literature, only SEED IV stands out (at 5.8%), which is interesting in that it adopts a discrete space of four emotions for classification (happy, sad, fear and neutral). Instead, each of the other datasets do not exceed 5% (MAHNOB [207] and DREAMER [59] (3.3%), CMEED and MPED [208] (1.7%), ASCERTAIN [209], MDME [210], and SDMN [211] (0.8%)).

Fig. 5. (c) offers a statistic about the interest of the authors on the studies examined in the various perspectives of emotion representation. As already mentioned in Section 1.3, the two dominant perspectives, and the only ones considered in the literature examined, are those based on categorical and dimensional models. More than 80% of the works are based on a representation of emotions, and then their subsequent classification in terms of valence and arousal (and only in one case also dominance [165]).

Finally, graph 5.(d) shows the percentage distribution according to the proposed taxonomy. Looking at this graph, it is evident that despite the majority of generalization studies still being tied to traditional approaches (34.2%), a significant percentage is moving towards the use of deep machine learning (Deep UDA CS), reaching 29.3%. This is followed by Shallow UDA SS approaches (9.8%), Deep UDA CSS (6.1%), Shallow UDA TS and Supervised DA (4.9%), IRS UDA (3.7%), Hybrid UDA and Deep DG (2.4%) and finally Shallow DG (1.2%).

The Table 2 provides a brief overview of different methods for quick comparison. For methods focused on Domain Adaptation, having data from the target domain is crucial. In specific applications, this means that new participants would need to go through initial data collection sessions. These sessions can also be particularly structured (calibrations) if labels beyond data are requested (Supervised DA). Recently, new methods are trying to lighten the calibration stage, by minimizing the quantity of data and labels to be collected (few shot methods). On the other hand, some DG strategies might offer *plug and play* solutions, but they rely on having a large amount of public data (in particular, in the case of Data-driven Transformation) not available so far. Furthermore, not all the data can be adapted to the Transfer Learning procedure, therefore a further data selection strategy can be part of the method. Concerning the output, certain strategies presume that a single feature projection space is sufficient to achieve good generalization performance, whereas others opt to construct multiple spaces with the belief to enhance generalization performance.

Regarding UDA methods, it is noteworthy that a significant portion of surveyed shallow UDA approaches focused on optimizing the Subspace Alignment (SA) discrepancy or the Maximum Mean Discrepancy (MMD) discrepancy. Particularly, MMD has garnered considerable attention in the literature as it enables the creation of a shared common space where both target and source domain data are projected. This differs from SA-based methods (or similar Target Similarity-Based methods), which seek a transformation to fit data from one domain to another, assuming that the existing domain can correctly represent all the data. On the other hand, numerous deep UDA methods leverage adversarial learning paradigms. The multilayer structure of DNNs allows the first layers to specialize in feature extraction, and the subsequent layers in classification. The former can be specialized to project the data into a suitable space where domain differences are minimized. Consequently, adversarial approaches appear to be the most

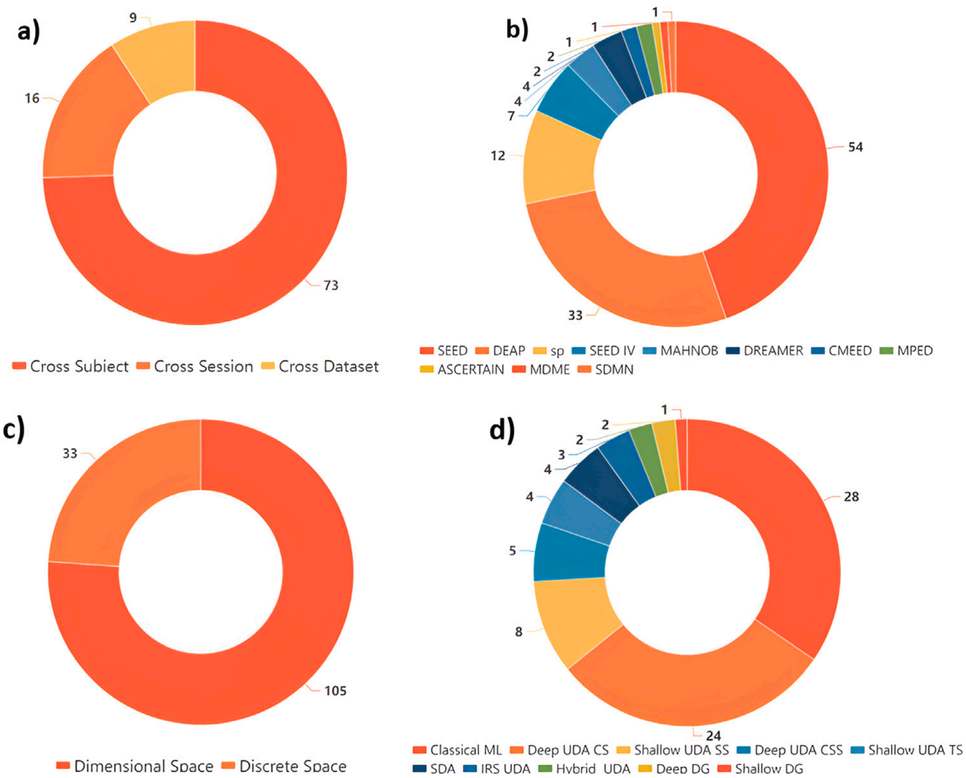

Fig. 5. Pie charts for distribution of papers occurrences according to: (a) generalization types, (b) used datasets, (c) emotional theories, (d) categories of the taxonomy.

Table 2
Comparison of the transfer learning methods according to the use of target data/labels and the processing procedure. 'X' indicates the properties of the methods.

	Target data exploitation	All target labels exploitation	Data-driven transformation	Data selection implementation	Single space generation	Multiple space generation
Shallow DG						
Deep DG			X			
Supervised DA	X	X	X			
Hybrid UDA	X		X	X		
IRS UDA	X		X	X		
Shallow UDA TS	X					
Shallow UDA SS	X				X	
Deep UDA CS	X		X		X	
Deep UDA CSS	X		X		X	X

commonly used technique in the literature to construct an appropriate set of extractor layers for this purpose.

In Table 4 all papers included in the review are reported, indicating if belonging to the proposed taxonomy or to classical ML methods. Moreover, for each research study as the type of generalization (cross-subject, cross-session, or cross-device), the EEG dataset, the adopted classifier (whether proposed as a personal contribution or adopted from the literature), and the validation strategy is reported. The best performer solutions in terms of mean classification accuracy are proposed in Table 3. Only cross-subject studies were considered, as most of the studies examined. Ten classification issues were focused on. Each issue is defined by considering the number and type of classes (binary and ternary on valence and arousal, quaternary on the two-dimensional valence-arousal plane, binary and quaternary on discrete dimensions) and the adopted dataset (DEAP, SEED, other). For each issue, the best performer study in terms of accuracy was identified. Only studies reporting both mean accuracy and standard deviation were included in the performance assessment. In Fig. 6 a timeline is depicted illustrating the development of the different methods. When at least one article is published, the method/year cell is gray. Each trophy is associated with the method (published paper) achieving the best performance in one of the clusters in Table 3.

Notably, to date, no robust electroencephalographic patterns are recognized in scientific literature for correlating with emotional states [212]. Some studies base their results on the asymmetry of scalp activations. In general, many theories still coexist and are not statistically well founded, as they are validated on small experimental samples [213–215].

When aiming for a generalization goal in EEG-based Emotion Recognition, TL methods are becoming more and more established in the literature. Domain Adaptation methods (Deep UDA CS, Shallow UDA SS, IRS UDA, Deep UDA CSS, Shallow UDA TS, and Supervised DA) exceed 60% of the total surveyed studies and exhibit very high accuracy performances in the table of best performers (see Table 3). In particular, Deep UDA CS is used by four best performer studies. This could be also due to the current massive use of this method in literature.

An emblematic case in this context is [112], namely the best performer in the classification issue on SEED IV with four discrete classes. This is an interesting study based on a self-organized graph construction module. This solution can be considered as a peculiar implementation of the well established adaptive filters strategy, when the generalization goal is pursued by customizing the network to the current input. Conversely, the DA strategies make the data belonging to different

Table 3
The most representative studies according to their classification accuracy, categorized by EEG dataset (SEED, DEAP, others), by number and type of classes considered. DIM = Dimensional; DIS = Discrete; sp = self-produced; VAL = valence; ARO = arousal; LV(A)/MV(A)/HV(A) = low/medium/high valence(arousal).

Proposed category	Study	Dataset	Reference theory	#Classes	Cross Subject accuracy	Input data	Preprocessing	Eval. data
CLASSICAL ML	[96]	DEAP	DIM (VAL)	#2 (LV/HV)	94.67 ± 12.01	DE	Customized Artifact Removal based on EMG and EOG	LOO
HYBRID UDA	[197]	DEAP	DIM (VAL)	#3 (LV/MV/HV)	68.06 ± 10.93	TFF + NL-DSF	Provided by DEAP[a]	LOO
DEEP UDA CSS	[204]	DEAP	DIM (VAL-ARO)	#2 (LV/HV) #2 (LA/HA)	73.90 ± 13.50 68.80 ± 11.20	DE	Provided by DEAP[a]	LOO
DEEP UDA CS	[162]	DEAP	DIM (VAL-ARO)	#4 (LALV-HALV-LAHV-HAHV)	62.66 ± 10.45	PSD + DE	Provided by DEAP[a] Samples with valence > 4.8 and arousal > 5.2 were discarded.	LOO, SU2SU O2OSE
DEEP UDA CS	[191]	SEED	DIM (VAL)	#2 (LV/HV)	97.66 ± 14.46	DE	Provided by SEED[b]	LOO
DEEP UDA CS	[164]	SEED	DIM (VAL)	#3 (LV/MV/HV)	90.92 ± 1.05	DE	Provided by SEED[b]	LOO
		Other	DIM (VAL-ARO)	#2 (LV/HV) #2 (LA/HA)	94.21 ± 5.88 88.03 ± 6.32	DE	Data was downsampled to 128 Hz, a bandpass frequency filter (4–45 Hz) was applied.	LOO
DEEP UDA CS	[161]	Other	DIS (HAPPY, SAD FEAR, ANGER)	#2 (JOY/SADNESS) #2 (JOY/ANGER) #2 (JOY/FEAR)	83.79 ± 1.55 84.13 ± 1.37 81.72 ± 1.30	DE	A band-pass filter (0.1–64.0 Hz) and a notch filter (50 Hz) were applied. Artifact removal based on FastICA.	LOO
CLASSICAL ML	[112]	Other	DIS (HAPPY, SAD FEAR, NEUTRAL)	#4 (HAPPY/SAD/ FEAR/NEUTRAL)	75.27 ± 8.19	DE	Data was downsampled to 200 Hz, a bandpass frequency filter (1–75 Hz) was applied.	LOO

[a] In DEAP, data was downsampled to 128 Hz, a lowpass frequency filter (0–75 Hz) and an EOG removal were applied.
[b] In SEED, data was downsampled to 200 Hz and a bandpass frequency filter (4.0–45.0 Hz) was applied.

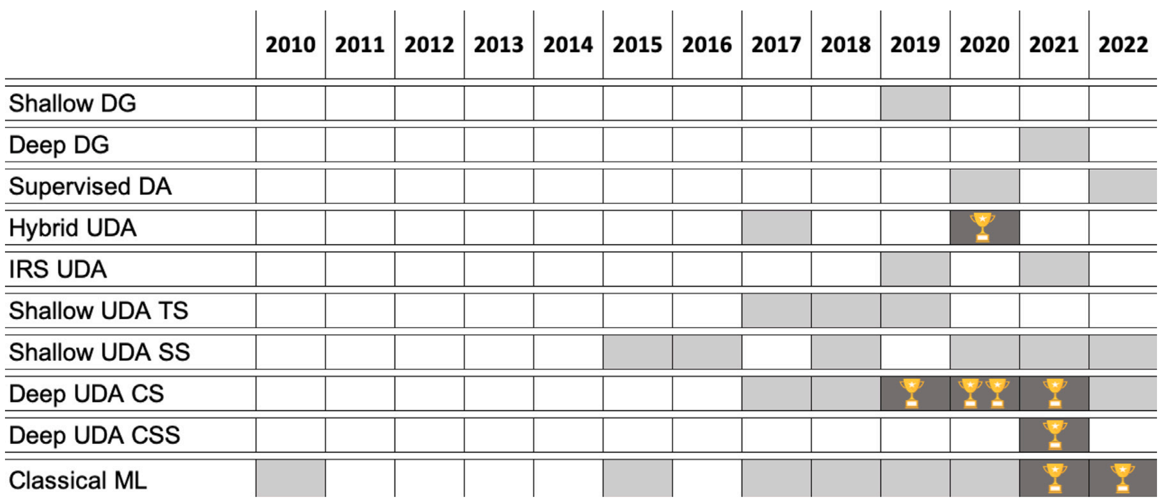

Fig. 6. Timeline of the different methods. When at least one article is published, the method/year cell is gray. Each trophy is associated with the method (published paper) achieving the best performance in one of the clusters in Table 3.

domains more homogeneous by means of appropriate transformations. The different impact between DA and adaptive filters approaches can be better appreciated by making a comparison between the previous study and [159]. Both studies address the problem of four-class classification on the same dataset by using a pipeline based on graphs and deep networks. In the first case, an adaptive graph is used without any DA methods, while the second study makes use of a (nonadaptive) graph approach in combination with DA techniques. Even though they use different approaches, the reported accuracy performances are comparable. This suggests how the dynamic search for feature extraction procedures represents an interesting frontier for future studies in this area, not excluding the potential of using this approach in combination with DA/DG techniques.

Challenges and potential solutions of the surveyed works

When applying TL methods to EEG data for ER tasks, it is important to consider various challenges. These include general challenges of using TL in EEG for ER, as well as specific challenges of each category within the proposed taxonomy of methods.

General challenges and potential solutions about TL in EEG-based ER

Regarding General challenges about the adoption of TL in EEG-based ER, we highlight the following:

- *Different theoretical backgrounds among the datasets:* A concern in the use of public datasets is its underlying theoretical background, often uncritically accepted by the scientists. Many studies validate the same machine learning algorithm on different datasets although the targeted psychic phenomena are radically different. Indeed, each dataset leverages on a specific theory of emotions and related experimental setup of emotion elicitation. For instance, DEAP is based on a dimensional approach and SEED IV on discrete one. Moreover, the documentation of the public dataset lacks information such as the cross-session temporal interval. This makes it difficult to distinguish if bias stemming from previous experience or personal states and environmental factors are

Table 4
Reviewed studies on generalization strategies for Emotion Recognition. Datasets used, classifiers, evaluation strategy (i.e. LOO = Leave-One-Subject/Session/Dataset-Out), and type of generalization (i.e. intersubjects, cross sessions and cross datasets) are presented for each entry in the table (sp = self produced, nl = not labeled; for the other abbreviations see Acronyms section).

Proposed category	Study	Dataset	Classifier	Evaluation strategy	Cross subject	Cross session	Cross dataset
	[93]	DEAP	TRFE	LOO	X		
	[81]	DEAP, MAHNOB	RF	LOO	X		X
	[82]	DEAP, SEED	SVM	LOO	X		
	[110]	SEED, DREAMER	DGCNN	LOO	X		
	[88]	DEAP, SEED	SVM	LOO	X		
	[89]	DEAP, sp	SBS	LOO	X		
	[92]	DEAP	TRFE	LOO	X		
	[99]	DEAP, SEED	VAE-LSTM	LOO	X		
	[102]	DEAP	SVM	LOO	X		
	[105]	DEAP, MAHNOB, DREAMER	SVM	LOO	X		
	[94]	DEAP, MAHNOB	RFE	LOO	X		
	[95]	SEED	DECNN	LOO	X		
	[101]	DEAP, SEED	VAE-LSTM	LOO	X		
CLASSICAL ML	[103]	SEED	SVM	LOO	X		
	[104]	SEED	SVM	LOO	X		
	[109]	ASCERTAIN	BiLSTM	LOO	X		
	[112]	SEED, SEED IV	SOGNN	LOO	X		
	[80]	SEED, sp	PTSVM	LOO		X	
	[96]	DEAP	RNN-EL	LOO	X		
	[75]	SEED-IV	OGSSL	LOO		X	
	[91]	DEAP, MAHNOB, DREAMER	SVM	LOO	X		
	[97]	SEED	DySampEns-SVM	LOO	X		
	[84]	sp	FA-NN	LOO	X		
	[90]	sp	SFS- VOTE	LOO	X		
	[76]	SEED-IV	sJSFE	LOO		X	
	[83]	sp	FCM	LOO	X		
	[86]	DEAP	DWT-SVM	LOO	X		
	[87]	sp	HAF-HOC	LOO	X		
	[194]	DEAP	SVM	LOO	X		
IRS UDA	[176]	DEAP	NCA	LOO	X		
	[199]	SEED	DMATN	LOO	X		
	[116]	SEED	ASFM	LOO	X	X	
SHALLOW UDA TS	[117]	SEED	MSSA	LOO	X		
	[33]	MDME, SDMN	RPCA	ASI		X	
	[119]	SEED	STM	LOO	X		
	[123]	SEED	TCA	LOO	X		
	[132]	SEED	SAAE	SU2SU, SE2SE, LOO	X	X	
	[130]	SEED	TPT	LOO	X		
SHALLOW UDA SS	[131]	DEAP, SEED	MIDA	LOO	X		X
	[124]	SEED	TCA	LOO	X		
	[127]	DEAP, SEED	DASRC	LOO		X	X
	[32]	sp	TCA	HO		X	
	[134]	SEED, MPED	GRU-MCC	LOO	X		
	[152]	SEED	DANN	LOO	X		
	[147]	SEED, SEED IV	DAN	LOO	X		
	[153]	SEED	BiDANN	LOO	X		
	[168]	DEAP	WGANDA	LOO	X		
	[141]	SEED	DDC	LOO	X		
DEEP UDA CS	[156]	SEED	R2G-STNN	LOO	X		
	[162]	DEAP, SEED	nl	LOO, SU2SU, O2OSE	X	X	
	[155]	SEED, SEED IV, MPED	BiHDM	LOO	X		
	[159]	SEED, SEED IV	RGNN	LOO	X		
	[161]	SEED, sp	TDANN	LOO	X	X	
	[163]	SEED, CMEED	A-DNN	LOO	X		
	[164]	DEAP, SEED, CMEED	ATDD-LSTM	LOO	X	X	
	[148]	sp	MSDAN	LOO	X		
	[190]	SEED	nl	LOO	X		
	[167]	SEED	nl	LOO	X		
	[174]	SEED	TDANN	SU2SU	X		
	[191]	DEAP, SEED	SDA-FSL	LOO	X		X
DEEP UDA CS	[175]	DEAP, SEED	MACI	LOO	X		X
	[157]	DEAP, DREAMER	AD-TCN	LOO	X		X
	[154]	SEED	BiHDM	LOO	X		
	[179]	DEAP, SEED	MDTDDL	LOO	X		X
	[172]	SEED	MMD-ER	LOO		X	
	[140]	SEED	JDAN	LOO	X		

(continued on next page)

Table 4 (*continued*).

Proposed category	Study	Dataset	Classifier	Evaluation strategy	Cross subject	Cross session	Cross dataset
DEEP UDA CSS	[23]	SEED	PPDA	LOO	X		
	[181]	SEED, SEED IV	MEERNet	LOO	X	X	
	[204]	DEAP, sp	DASC	LOO	X		
	[183]	SEED	MS-MDA	LOO	X	X	
	[182]	SEED	wMADA	LOO	X		
HYBRID UDA	[34]	sp	GNB	ASI		X	
	[196]	DEAP, SEED	PLRSA	LOO, SU2SU	X	X	
	[197]	DEAP	ESN	LOO	X		
SUPERVISED DA	[41]	DEAP, SEED, sp	nl	LOO	X		X
	[143]	DEAP, SEED	RCNN	LOO	X		X
	[186]	DEAP, SEED	Densenet	LOO	X		
	[192]	SEED, DEAP	FLADA	LOO	X		
SHALLOW DG	[202]	SEED	DG-DANN, DResNet	LOO	X		
DEEP DG	[205]	DEAP, SEED	BiVDANN	LOO	X		
	[206]	SEED	MBN	LOO	X		

the prevalent source of uncertainty. Furthermore, it is not possible to control confounding due to circadian rhythms because the experiments (both cross-session and cross-subject) are conducted without keeping the phase of the day fixed. Finally, at present, the available public datasets do not adopt an established practice of psychological screening of the subjects involved. In general, studies on EEG-based emotion assessment could benefit from administering psychometric questionnaires to participants. Indeed, psychological data could help to understand individual differences in emotional response, leading to clustering of subjects [204]. Recently, unsupervised clustering based on large datasets is emerging as a promising strategy for empirical identification of personality types [216]. Meanwhile, correlations have been found between personality types and EEG patterns [217]. Moreover, prior psychological assessments allow to manage bias due to individual traits or states. The introduction of psycho-metric tests and assessments during the production of upcoming datasets could lead to a much more fruitful use of data in support of generalization.

- *Multi-source as single source:* a large part of DA strategies uses the source data as they all belong to the same domain. This assumption can be too strong, especially if the source data are acquired in different sessions or, worse, from different subjects. This point is taken into account by multi-source DA approaches, such as Transductive Parameter Transfer (TPT) [218], or by multi-source DA approaches specific for EEG data, such as MSSA or MEERNet, where different source subjects/sessions are considered as different source domains, and by DG methods.

- *Methods designed in different contexts:* originally, several well-known TL methods were developed outside the Emotion Recognition framework. In recent years, several studies have exploited these methods in ER but focusing only on their effectiveness, without conducting an in-depth analysis of the specific contributions made by TL methods in this field. In fact, several DA pipelines consist of several steps, and a comparison of performance with and without TL methods does not identify the most effective steps. For example, in [219] it is shown that in several cases the data normalization adopted as first step of several TL pipelines has a stronger impact on the model generalization respect to the TL methods themselves. Other studies [104,105] have confirmed that simple data normalization with low computational and spatial efforts allows for interesting results in EEG-based Emotion Recognition, in some cases comparable or better than several current DA/DG approaches. In general, the merits of TL techniques are not in question, but in the future, a more in-depth analysis by scientists is needed, for example by accompanying their proposals with ablation studies.

- *Challenges in online use:* most TL methods discussed in the literature rely on target data that is available before the model is actually deployed, or at the very least, require calibration data. This availability is not granted due to additional efforts both for the subjects and the operators. However, certain applications can benefit from adapting themselves in real-time using data collected during active usage [220]. However it is important to consider that, even in this scenario, the non-stationarity of EEG signals presents a significant challenge, as it may lead to variable data distributions even within the same session. Consequently, new strategies like Online Transfer Learning (OTL, [220,221]) or DG techniques able to capture and leverage the general characteristics of the data should be explored by the scientific community.

- *Quality of the acquisition devices:* another point to take into account is that the proliferation of EEG acquisition devices on the market is not always coupled with consistency in terms of quality between the various devices (considering electrode type and positioning, interference shielding, signal-to-noise ratio, amplification strategies, etc.). A comparison among different studies must take into account the quality of EEG instrumentation used. The IEC 60601-2-26 standard applies to basic safety and essential performance of electroencephalographs used in a clinical environment. Among the requirements, the minimum overall signal quality for an electroencephalographic device to be considered acceptable is defined [222]. Even if IEC 60601-2-26 is a standard specifically developed for clinical purposes, it is nowadays the only available standard for EEG instrumentation quality certification. In the future, it is desirable for research to be increasingly based on certified instruments. However, an encouraging trend emerges from the most recent public datasets. Indeed, they are all based on standardized equipment: (i) Neuroelectrics Enobio 8 in the case of LUMED [41], (ii) NuAmp Neuroscan in the case of CMEED [164], and (iii) gtec.HIamp in the case of the dataset produced by [161].

Specific challenges and potential solutions about TL in EEG-based ER

Specific challenges can be highlighted for each DA category of the proposed taxonomy. In particular:

- *DA methods challenges:* in several DA strategies labels of both the source and target domains are not considered in the alignment of the domains. This type of DA methods can lead to overlapping distributions of source and target domains, without any consideration on the belonging classes. As a consequence, the class separability can worsen. This can be a weakness of some shallow UDA methods, such as unsupervised TCA. UDA methods require the availability of unlabeled target data in the training phase. In the Emotion Recognition problem, this implies that EEG recordings belonging to the target session/subject are provided. This availability is not granted, especially in online applications. In alternative, initial calibration data can be acquired from the target subject, but this requires additional efforts both for the subjects and the operators. Furthermore, Shallow UDA methods require data projections between different spaces by means of handcrafted transformations. Therefore, the adopted transformations may not be suitable for the available data. Moreover, among proposed data transformations, some of them require all the data be processed together, with a large amount of memory needed. On the other side, Deep UDA methods require a greater number of parameters with respect to a shallow method. This can result in high computational complexity, such as in MACI and Adversarial learning-based methods. This can lead toward overfitting and the curse of dimensionality problems [129] if not enough data are available. However, despite their high computational load, Deep UDA methods exhibit the best performance in terms of accuracy at least in four of the cases considered, as can be seen in Table 2. Regarding Supervised DA methods, several of them require ML models pre-trained on data belonging to the source domain. In several tasks (such as image classification) several models pre-trained on big amount of data are freely and publicly available to the user (for example ResNet models trained on ImageNet [142]). However, it is harder to find similar models trained on EEG data for ER task. This can be due to the scarcity of publicly available large dataset. Moreover, also by collecting together several public dataset, the resulting model may have low performance. Indeed, being the EEG is a highly non-stationary signal, it results very susceptible to different experimental conditions. Finally, Instance Reweighting and Selection methods select or score data to manage uncorrelation between source and target data. Therefore, a part of the data may not fully used in the training stage, making these methods strongly dependent on the score/selection function adopted. Moreover, their computational cost may be not negligible, since they re-weight the available data according to their similarity.

- *DG methods challenges:* in contrast to DA approaches, the aim of DG is to generalize over several domains. Therefore, data belonging to the target may not be required in the training stage. Instead, data from several other domains (i.e. sessions/subjects) are required. This may be impractical especially in experimental scenarios, due to the difficulties of enrolling subjects and the time required to conduct multiple acquisitions. Thus, DA approaches are currently the most proposed methods in Emotion Recognition scenarios involving TL.

7. Conclusion

In this work, a systematic literature review collecting papers on machine learning strategies to pursue (cross-subjects and cross-sessions) generalizability in EEG-based Emotion Recognition was carried out. Among the 418 articles retrieved from Scopus, IEEE (Institute of Electrical and Electronics Engineers) Xplore, and PubMed databases, 75 papers resulted eligible. Furthermore, the studies with the best results in terms of average classification accuracy were identified, and the ten best results considering as many classification problems were highlighted.

Most of the analyzed works adopted Classical ML or TL approaches to deal with the generalization problem. In particular, TL methods received a considerable attention from the scientific community, as their basic framework is particularly suited to the EEG Emotion Recognition generalization problem. In spite of their limitations (i.e., the need for target data during the training stage), today DA methods result to be particularly encouraging to handle the EEG Emotion Recognition generalization problem. DG methods aim to achieve a more generalized approach compared to DA, which relies on target data availability. However, due to the challenging nature of this approach, current DG methods generally have lower performance than DA approaches in the task of Emotion Recognition. Finally, works relying on simple ML methods combined with proper normalization strategies lead to interesting results with a low computational load. This can be due to the ability of some simple transformations to project data into spaces where shared characteristics between the domains are emphasized.

An interesting perspective based on self-organized graph construction modules emerged as peculiar strategy. This suggests how the adaptive feature extraction procedures represent an interesting frontier for future studies in this area, not excluding the potential of using this approach in combination with DA/DG techniques.

Future research on EEG-based emotion assessment could also benefit from administering psychometric questionnaires to participants in order to conduct a psychological screening of the experimental sample [223]. This could help to understand individual differences in emotional responses, leading to clustering of subjects also taking into account the different subjects' personality.

Acronyms

A-DNN - Adversarial Deep Neural Network
AD-TCN - Adversarial Discriminative Temporal Convolutional Network
ASFM - Adaptive Subspace Feature Matching
ASI - Add-Session-In
ATDD-LSTM - Attention-based LSTM
BiDANN - Bi-hemispheres DANN
BiHDM - Bi-Hemispheric Discrepancy Model
BiLSTM - Bidirectional LSTM
BiVDANN - Bi-lateral Variational Domain Adversarial Neural Network
CS - Common Space-based
CSS - Common+Specific Space-based
DAN - Deep Adaptation Network
DANN - Domain Adversarial Neural Network
DASC - Domain Adaptation Subject Clustering
DASRC - Domain Adaptation Sparse Representation Classifier
DDC - Deep Domain Confusion
DE - Dynamic Entropy
DECNN - Dynamic Empirical Convolutional Neural network
DGCNN - Dynamical Graph Convolutional Neural Networks
DG-DANN - Domain Generalization DANN
DResNet - Domain Residual Network
DWT - Discrete Wavelet Transform
DySampEns-SVM - Dynamic Sample Entropies-SVM
EOG - Electrooculography
ER - Emotion Recognition
ESN - Echo State Network
FA-NN - Factor Analysis Neural Network
FCM - Fuzzy-C-means
FLADA - Few-Label Adversarial Domain adaption
GNB - Gaussian Naïve Bayes
GRU-MCC - Gated Recurrent Unit-Minimum Class Confusion
HO - Hold Out
HAF - Hybrid Adaptive Filtering
HOC - Higher Order Crossings
IRS - Instance Reweighting and Selection
JDAN - Joint Distribution Adaptation Network
LOO - Leave-One Subject/Session/Dataset-Out
LSTM - Long short-term memory
MACI - Multi-Source Co-adaptation Correlation Information
MBN - Multi-Branch Network
MDTDDL - Multi-source Domain Transfer Discriminative Dictionary Learning modeling
MEERNet - Multi-Source EEG-based Emotion Recognition Network
MIDA - Maximum Independence Domain Adaptation
MMD - Maximum Mean Discrepancy
MSDAN - Multi-Spatial Domain Adaptation Network
MS-MDA - Multi Source-Marginal Distribution Adaptation
MSSA - Multi-Subject Subspace Alignment
Na - not available
NCA - Neighborhood Component Analysis
NL-DSF - Nonlinear - Dynamical System Features
O2OSE - ONE-TO-ONE-SESSION
OTL - Online Transfer Learning
OGSSL - Optimal Graph coupled Semi-Supervised Learning
PLRSA - Progressive Low-Rank Subspace Alignment
PPDA - Plug-and-Play Domain Adaptation
PSD - Power Spectral Density

R2G-STNN - Regional To Global Spatial-Temporal Neural Network
RCNN - Residual CNN
RF - Random Forest
RFE - Recursive Feature Elimination
RGNN - Regularized Graph Neural Network
RNN-EL - Recurrent Neural Network and Ensemble Learning
RPCA - Robust Principal Component Analysis
SAAE - Subspace Alignment Auto Encoder
SBS - Sequential Backward Selection
SFS-VOTE - Sequential Feature Selection-VOTE
SDA-FSL - Single-Source Domain Adaptive Few-Shot Learning Network
SE2SE - session-to-session
sJSFE - semi-supervised Joint Sample and Feature importance Evaluation
SOGNN - Self-Organized Graph Neural Network
sp - self-produced
SSB - Shared Space-Based
STM - Style Transfer Mapping
SU2SU - subject-to-subject
SVM - Support Vector Machine
TCA - Transfer Component Analysis
TDANN - Two-Level Domain Adaptation Neural Network
TFF - Time–Frequency Features
TPT - Transductive Parameter Transfer
TRFE - Transferable Recursive Feature Elimination
TSB - Target Space-Based
UDA - Unsupervised/Semi-supervised Domain Adaptation
VAE - Variational Auto Encoder
WGANDA - Wasserstein Generative Adversarial Network Domain Adaptation
wMADA - Wasserstein-Distance-based Multi-Source Adversarial Domain Adaptation

CRediT authorship contribution statement

Andrea Apicella: Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Pasquale Arpaia:** Supervision. **Giovanni D'Errico:** Conceptualization, Data curation, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Davide Marocco:** Conceptualization, Formal analysis, Investigation, Methodology. **Giovanna Mastrati:** Conceptualization, Data curation, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Nicola Moccaldi:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Roberto Prevete:** Conceptualization, Formal analysis, Methodology, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Giovanna Mastrati reports financial support was provided by INPS - National Social Security Institution. 0000-0002-5192-5922 reports financial support was provided by European Union.

Data availability

No data was used for the research described in the article.

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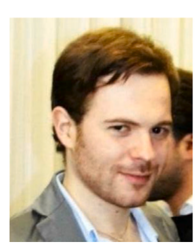

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