Advancing Emotion Recognition: A Systematic Review of Emotion Induction Techniques and Machine Learning Approaches

Meryem Bekler[1], Murat Yilmaz[1], Paul Clarke[2,3]

[1]Gazi University, Department of Computer Engineering, Ankara, Turkey
meryem.bklr@gmail.com, my@gazi.edu.tr
[2]School of Computing, Dublin City University, Dublin, Ireland
[3]Lero, the Irish Software Engineering Research Center
paul.m.clarke@dcu.ie

Abstract. Emotion plays a pivotal role in human-computer interaction, making accurate recognition and effective induction of emotions crucial for developing systems that can understand and respond to human emotions. This paper surveys 31 existing papers in the literature, focusing on emotion induction techniques, data collection types, emotion models, and machine learning methods employed in emotion recognition. According to evaluations, researchers commonly rely on visual stimuli and dimensional emotion models. EEG signals enjoy considerable popularity among various modalities, and the prevalent trend in machine learning approaches involves the use of Support Vector Machines (SVM). This paper aims to contribute to the field by analyzing the recent trends in emotion recognition and induction and be a guide for future research.

Keywords: Emotion recognition, emotion induction, emotion models, machine learning.

1 Introduction

Although the concept of emotion is widely recognized and often discussed, there is no universal agreement on its definition, leading to varied interpretations and understandings of what an emotion is [1]. There is widespread acceptance of the componential structure of emotion including mental and bodily components [2]. A componential definition of emotion, which is named as the Component Process Model (CPM), defines emotion as a sequence of interconnected, synchronized changes in the states of all or most of the five organismic subsystems in reaction to the assessing an internal or external stimulus event as significant to the organism's primary interests [1, 3]. According to this definition, an emotion comprises a collection of various interrelated changes within the following five different components: (i) cognitive, (ii) motivational, (iii) physiological, (iv) behavioral, and (v) experiential (feeling) [1].

The universal relevance of emotions in daily life has led to the development of Affective Computing (AC). This interdisciplinary field strives to create systems and devices capable of recognizing, interpreting, processing, and reacting to human emotional states. [4]. The central motivation of AC stands on the idea that emotions play a crucial role in forecasting the mental state and future behaviors of humans. Thus, AC can significantly enhance the performance of computer-based systems in recognizing and responding to human emotions [5, 6].

Emotion recognition and emotion induction have key roles for improving AC [7]. Emotion recognition involves accurately figuring out emotions from different sources like facial expressions, gestures, speech, and more, while emotion induction intentionally triggers specific emotional reactions using various methods [8]. These play important roles in diverse fields such as psychology [9], physiology [10], healthcare [11], safe driving [12], education [13], and marketing [14].

This study systematically reviews emotion recognition and induction research, emphasizing emotion models and machine learning methods from 2019 to 2023. Given the growing popularity of this interdisciplinary field and the increasing number of studies, it is crucial to identify, evaluate, and synthesize research results for future advancements. Focusing on the past five years, the goal is to implement the latest state-of-the-art works and methods.

2 Background

2.1 Emotion Induction Techniques

Emotion induction techniques play a pivotal role in experimental settings aimed at eliciting and studying emotional responses. Commonly utilized methods include viewing pictures, watching videos, listening to music, reading emotional text, recalling past experiences, or imagining an emotional event [15]. These techniques are considered as passive induction as they require passive involvement of individuals in a controlled setting offering benefits, such as controlling the stimuli presented, standardizing measurement conditions, and minimal risk of external factors interfering with the results [16].

Emotion induction aims to gather data that provide indications for identifying the elicited emotions. Facial expressions, physiological changes, biosensors data such as Electroencephalogram (EEG), Electrocardiogram (ECG), Electromyography (EMG), Electrodermal Activity (EDA), Skin Temperature (SKT), and Galvanic Skin Response (GSR) are mostly used to measure emotions.

2.2 Emotion Models

Several models of emotion have been developed to understand and categorize human emotions. These models can be classified into two categories: discrete and dimensional. Discrete models propose the existence of distinct, basic emotions. According to the discrete model, each emotion differs based on its unique characteristics [4]. Dimensional models consist of continuous dimensions that propose emotional states are composed of several changes in psychological and physiological dimensions, such as valence, arousal, and control (or dominance/power) [17]. Arousal refers to the strength or intensity of an emotional state, ranging from high to low. Valence means the positivity or negativity of an affective state. The control/dominance dimension describes the degree of influence or control over the situation [17].

Ekman's Basic Emotion Theory is an example of discrete models, and it proposes that certain emotions appear universally recognized apart from the cultural background and identifies six basic emotions: anger, disgust, fear, happiness, sadness, and surprise [18]. Plutchik's Wheel of Emotion is another example which categorizes eight basic emotions: trust, surprise, joy, fear, disgust, sadness, anticipation, and anger [19].

In case of dimensional models, the Circumplex Model of Affect (CMA) categorizes emotions into a two-dimensional circular space [20]. The vertical axes represent arousal, and the horizontal axes represent the valence dimension. These two axes divide the space into four quadrants. Another two-dimensional model is the Geneva Emotion Wheel (GEW). It categorizes 20 distinct emotions [21]. The GEW measures emotional reactions to objects, events, and situations. It places emotion families in a circle, with intensity bubbles ranging from 0 to 5 [17]. Finally, all three dimensions unite in a three-dimensional model, Valence-Arousal-Dominance (VAD) [22].

2.3 Related Work

In recent years, researchers have conducted studies on emotion recognition and induction with the aspect of emotion models and machine learning methods. Duville et al. [23] presented a systematic literature review (SLR) that focuses on emotion recognition and regulation using electrophysiological signals. They selected a total of 42 articles from 2014-2020. In the articles examined, attention was paid to the presence of at least one of the emotional models and the usage of electrophysiological signals. Prabowo et al. [24] introduced an SLR of 107 primary studies between 2017 and 2023 to explore data trends, classifiers, and contributions to emotion recognition using EEG signals. Ortmann et al. [25] identified 21 works out of 256, including facial expression recognition in virtual reality scenarios. Tomar et al. [26] provided a SLR on existing modalities for emotion recognition, emotion models, and trends in relevant studies by selecting articles published from January 2010 to June 2021. The final 129 articles were reviewed according to research questions. Leszczelowska et al. [27] performed an SLR including over 40 articles to identify the commonly used datasets, electrodes, algorithms, and EEG features, as well as their extraction and selection methods. Sutedja et al. [28] studied the efficient methods of implementing facial expression recognition using a SLR, reviewing 20 papers. In addition to these works, other SLR examples focus on emotion recognition from EEG signals and facial expressions. From this, machine learning methods were explored only focusing on specific data modalities. We aim to search articles including any data modalities without focusing on a specific one.

In this study, we aim to review the recent studies on emotion recognition and induction to get insight into trending machine learning methods used for emotion recognition and popular emotion induction techniques.

3 Review Methodology

This section presents an overview of our research methodology followed by an overview of the systematic approach according to PRISMA guidelines [29]. It is an evidence-based reporting system designed to analyze all published reports related a specific subject to find answers to predetermined research questions. Various inclusion and exclusion criteria are determined to identify the reports to be included in the SLR. Then, the findings are synthesized.

3.1 Research Questions

This work focuses on emotion recognition and emotion induction with a focus on emotion models and machine learning methods, aiming to highlight the most frequently used induction techniques, modalities, and machine learning techniques.

Our research questions are as follows:

RQ1: What are the most frequently used emotion induction techniques in emotion recognition?

RQ2: Which emotion models are mostly used in classifying emotions?

RQ3: What are the types of data collected to analyze?

RQ4: What machine learning methods researchers prefer for emotion recognition? What are the recent trends?

3.2 Inclusion and Exclusion Criteria

In this study, we surveyed the articles from the journals, and conferences published in the English language from 2019 to 2023. It is important to highlight that to be included in this review study, an article must satisfy all inclusion criteria and not meet any of the exclusion criteria. For this study, the following inclusion and exclusion criteria were applied to all the retrieved papers:

Inclusion criteria.

- Studies that are relevant to subject and published between 2019 and 2023.
- Full-text papers.
- Papers written in English language.

Exclusion criteria.

- Studies that are irrelevant to subject.
- Papers published before or after the given period.
- Uncompleted studies.
- Book chapters.
- Unavailable full-text research papers.
- Papers not written in English Language.
- Master or doctoral dissertations.
- Pre-print articles.

- Workshop descriptions.
- Reviews. Surveys.
- Conference proceedings.

3.3 Study Selection Process

The process began with electronic searches of studies published in English from 2019 to 2023 in Google Scholar, IEEE, ScienceDirect, ACM, and Springer databases. The following keywords were employed to search in the databases: emotion recognition, emotion induction, emotion models, emotion frameworks, and machine learning. As query sentence (“emotion recognition” AND “emotion induction” AND (“emotion models” OR “emotion frameworks”) AND “machine learning”) was used.

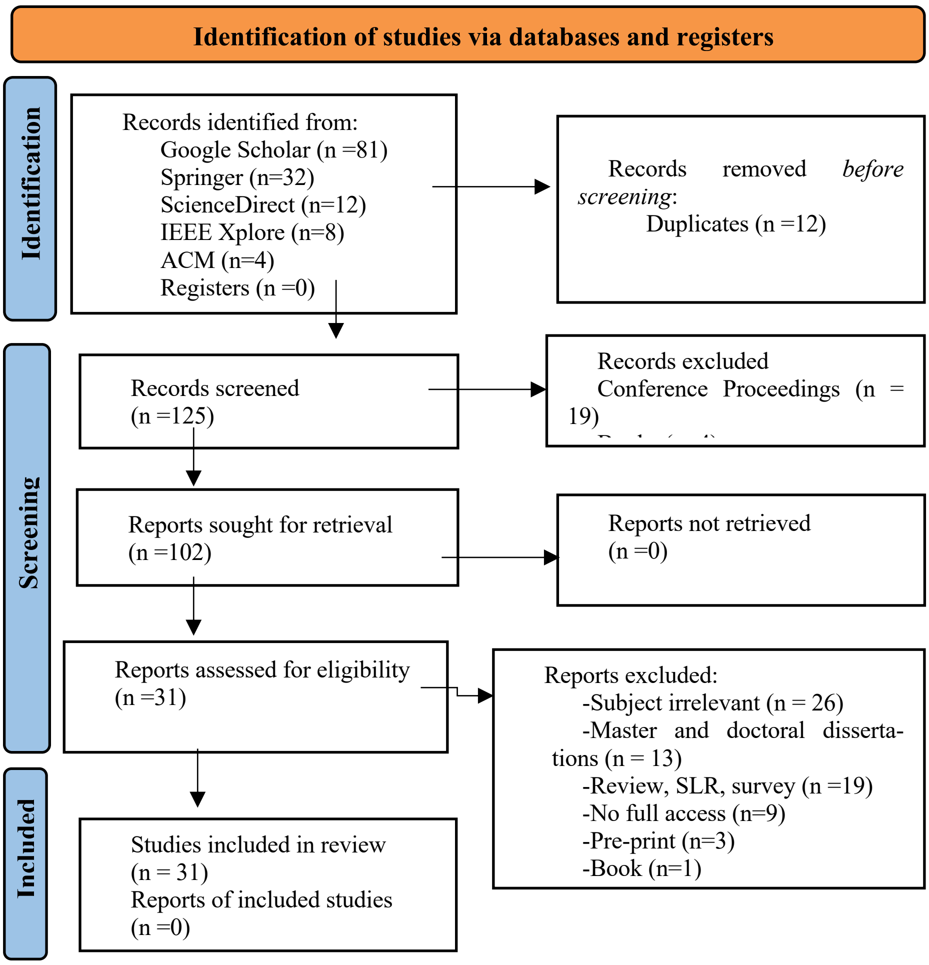

Fig. 1. Records identified from each database and exclusion according to criteria [61].

The search retrieved 137 results. 81 from Google Scholar, 8 from IEEE Xplore, 12 from ScienceDirect, 32 from Springer, and 4 from ACM. From these studies, only those which satisfied our inclusion and exclusion criteria have been included in this SLR. Duplicate studies and studies which use only statistical methods instead of machine learning were excluded. After employment of these inclusion and exclusion criteria, 31 articles were included in this work (see Fig. 1.).

4 Results and Discussion

In this section, the results of the SLR study are briefly presented. Here, we stated the answers to our four research questions in the selected 31 articles.

When the chart was investigated, a general upward trend becomes apparent (see Fig. 2.). It has been observed that in years that do not conform the general trend, a periodic reduction is observed in the quantity of publications derived from the query and deemed within the scope.

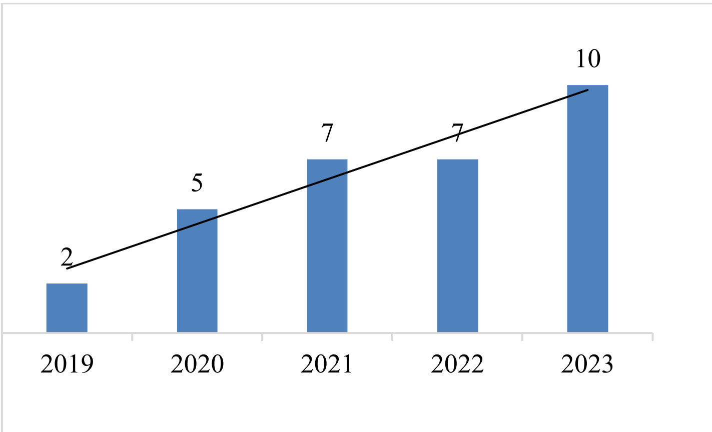

Fig. 2. The distribution chart by years.

4.1 RQ1: What are the most frequently used emotion induction techniques in emotion recognition?

In the context of RQ1, that aims to identify the most frequently used emotion induction techniques by researchers, the reviewed studies were evaluated. A notable trend emerged from the evaluation, indicating a predominant utilization of video clips as the primary induction paradigm across the reviewed studies. This consistent pattern highlights the importance of visual stimuli in evoking emotional responses.

Researchers have a significant preference for the dynamic and multi-modal nature of video-based stimuli. Videos offer a wealth of information beyond just the visual content. They also capture facial expressions, body language, and context, all of which are crucial for recognizing emotions. This multifaceted nature of video allows for a more comprehensive understanding of emotional states compared to static images or textual descriptions.

One of the reasons that make video clips preferable for researchers can be that videos allow researchers to control and manipulate the stimuli that participants are exposed to. This makes it possible to create controlled experiments and isolate the effects of specific factors. Also, videos are available and easily can be accessed online. This makes it easy for researchers to collect large datasets of video stimuli and study emotion recognition in a variety of context. Compared to self-reported measures, videos minimize subjectivity. And the most significant thing is that videos offer a more ecologically valid way to study emotion recognition compared to other static stimuli types. All these features seem to make video clips favorite choice of stimuli for researchers.

In addition, pictures also are employed, following video clips. From this, it can be said that visual stimuli, namely, videos and pictures are the most preferable induction techniques. They are both can be edited and manipulated to increase the emotional impact. However, compared to video clips, pictures have a static nature and they capture a single moment unlike video clips which are more engaging with the combination of visual and audio elements. With all these advantageous features, researches prefer video-based stimuli.

Table 1. Emotion Induction Techniques

Stimulus	Article References
Video Clips	[32], [33], [34], [35], [36], [42], [43], [44], [45], [56], [57]
Pictures	[30], [41], [42], [49], [51], [60]
Gameplay	[31], [39], [48]
Music, Audio	[37], [50], [52], [54], [59]
Driving Simulator	[47], [58]
VR Games	[40]
VR Applications	[46]
Breathing exercises (unguided/guided)	[53]
Autobiographical Recall	[55]

In addition to the visual stimuli, it was observed from Table 1. that autobiographical recall, VR applications and games are less frequently used induction techniques. It can be inferred that the potential of VR is being explored in various contexts, including as an induction technique. However, the observation that these VR techniques are less frequently used, in comparison to visual stimuli, may indicate that there is still ongoing exploration and experimentation with the application of VR in the given context.

4.2 RQ2: Which emotion models are mostly used in classifying emotions?

When emotion models were evaluated to be able to answer RQ2, it was observed that dimensional models have superiority over discrete models (see Table 2) in emotion classification.

In studies that no specific emotion model is defined, researchers employed a binary classification method. For example, in [46, 53], emotions were classified as either stress or no-stress, while [30, 37, 41, 42, 57] utilized a categorization into negative and positive emotions. In the study described in [47], participants, using a driving simulator, were categorized as either frustrated or not.

Due to the continuous nature of emotions, dimensional models capture this dynamic structure of emotions, allowing for a more detailed representation of emotional experiences. While discrete emotion models simplify emotions by placing them into a restricted set of categories, dimensional models enable researches to label emotions in a more detailed manner. With these advantageous features of dimensional models over discrete ones, researchers more likely to prefer dimensional models in their studies. While dimensional models offer advantages, it is necessary to note that the choice of model type depends on the specific application and goals of emotion recognition.

Table 2. Emotion Models

Model Type	Article References
Dimensional	[30], [31], [32], [36], [40], [45], [46], [47], [48], [51], [56], [58], [59]
Discrete	[27], [28], [35], [39], [44], [50], [60]
Both Discrete and Dimensional	[29], [34], [41]
Binary Classification	[26], [33], [37], [38], [42], [43], [49], [57]

Among all dimensional models, CMA is the most frequently used model. It is a two-dimensional model based on valence and arousal. VAD combines three dimensions, namely, valence, arousal, and dominance(control). The distribution of dimensional studies is shown in Fig. 3.

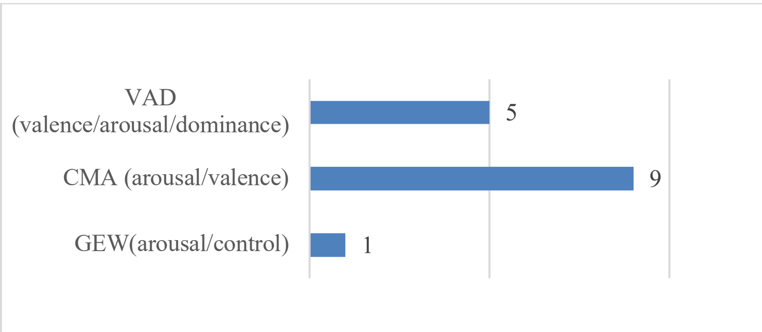

Fig. 3. Distribution of Dimensional Models.

4.3 RQ3: What are the types of data collected to analyze?

In almost all reviewed studies, participants were asked to rate the intensities of stimuli using scales such as Self-Assessment Manikin (SAM) or Differential Emotion Scale (DES). From this knowledge, participants' self-assessments are always significant data sources for researchers.

In the overall evaluation, aside from self-assessment answers, EEG signals were researchers' favorite data sources. Following that, GSR signals and facial expressions were also popular data sources for emotion recognition studies. As an answer for RQ3, a detailed distribution of studies by data types can be seen in Table 3.

Biosensor data such as EEG, ECG, and GSR provides objective measurements, reducing reliance on self-reporting data. As physiological responses are less sensitive to bias that arise from self-reporting, this objectivity enhances the emotion recognition. Unlike facial expressions, which can be intentionally faked by individuals, EEG and ECG represent physiological signals that cannot be consciously controlled by the person. The characteristic properties of EEG data give clues why it is favored in research studies, providing insights into an individual’s emotional states naturally, without the possibility of intentionally deception.

Table 3. Data Types

Measurements	Article References
Facial Expressions	[30], [33], [34], [40], [47], [48]
Keystroke	[30], [52]
Speech	[30], [38]
EEG	[31], [32], [34], [35], [36], [37], [40], [41], [42], [44], [45], [50], [51], [53], [56], [57], [58], [59], [60]
GSR or EDA	[30], [34], [40], [43], [46], [48], [55]
ECG	[40], [43], [45], [46], [49]
Wrist Pulse Signal (WPS)	[39]
Skin Temperature (SKT)	[30], [40], [43], [55]
Heart Rate (HR)	[40], [43], [47]
EMG	[46]
Blood Volume Pulse (BVP)	[30], [48], [55]
Acceleration	[40], [55]
Eye Tracking	[60]

4.4 RQ4: What machine learning methods researchers prefer for emotion recognition? What are the recent trends?

To be able to answer RQ4, the reviewed studies were evaluated in the context of machine learning methods. In most of the studies, not only one method was used but more. The results showed that Support Vector Machine (SVM) classifier was the most favorite machine learning method by researchers [34, 35, 36, 39, 40, 44, 45, 46, 47, 49, 51, 54, 57, 58]. In addition to SVM, K-Nearest Neighbors (KNN) [32, 34-36, 42, 44, 46, 49, 51], Random Forest (RF) [34, 36, 46, 49, 51, 52, 56, 58], Naïve Bayes (NB) [32, 35, 36, 46, 49, 54], Decision Tree (DT) [36, 46, 49], and Logistic Regression (LR) [51, 59] were other machine learning methods.

Besides, it can be seen from the evaluation (see Fig. 4.) that neural networks such as CNN [41, 50], LSTM [30, 34, 53], CNN-LSTM [37], ANN [36, 42, 48, 51, 54, 58], CNN-based EDL [43], 3D-CNN [34], Multilayer Perceptron (MP) [46] were employed. Deep learning is a subset of machine learning that focuses on using neural networks with multiple layers, to learn and make predictions from data. The reviewed studies indicates that deep learning methods give promising results on emotion recognition. The distribution of methods that were used in the studies can be seen in Fig. 4.

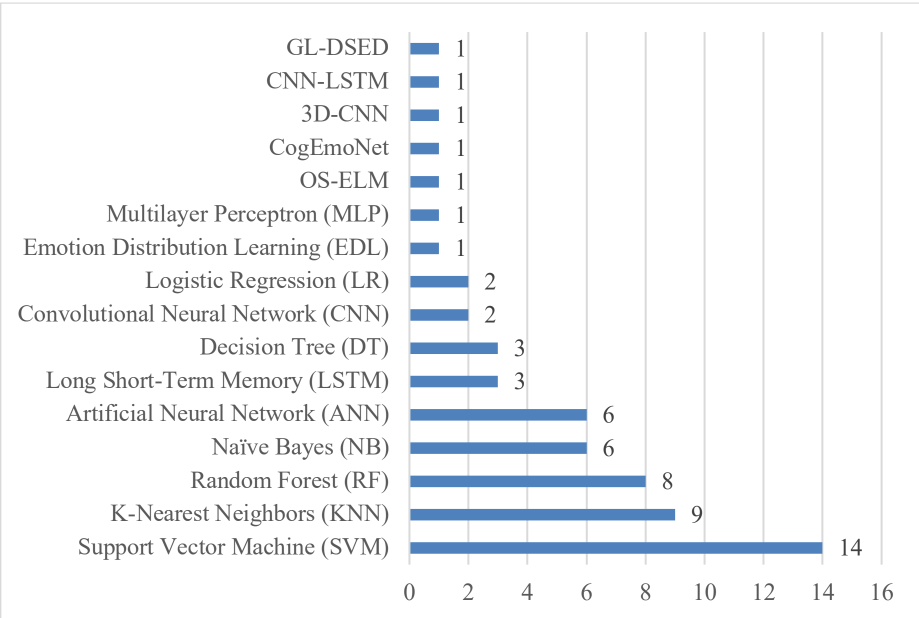

Fig. 4. The distribution of methods that were used in the studies.

The success of the selected machine learning methods changes according to the selected emotion measurements. In the studies which SVM was used, high accuracy rates were observed. However, it is hard to generalize accuracies. The rates change across datasets and measurements. In [39], SVM classifies discrete emotions (anxiety, pain, boredom, reference) with a maximum accuracy rate of 100%, using wrist pulse signals (WPS) collected with game induction. But, in [46], SVM classifies stress and no-stress states with a maximum accuracy of 63.98%, using ECG, EMG, and GSR data provided from a VR application. Examples propose that accuracy rates of SVM change across dataset features, selected emotion model, and induction techniques.

There is an increasing trend in employment of neural network architecture in emotion recognition studies. Neural networks also show high accuracy rates. In [42], ANN was used to classify positive and negative valence from EEG data from visual stimuli with 96.1% accuracy, while 80.2% for KNN. In [36], ANN classifies EEG signals according to arousal-valence model with a maximum accuracy rate of 60.4%, while 98.2 % for RF with a better performance.

From these results, it is not possible to definitively conclude whether classical machine learning methods or neural networks are superior in performance. They both perform differently according to the selected dataset, measurements, and emotion model. Researchers should therefore choose the method that best aligns with their specific objectives and research framework.

5 Conclusions

The study set out to gain a better understanding of emotion induction techniques, emotion models, and machine learning models. The findings revealed video clips as the most prevalent emotion induction technique, with VR and games being less favored. Dimensional models, particularly the CMA, emerged as superior for identifying emotions with multi-components. EEG signals were widely adopted due to their ability to capture uncontrollable brain activity, offering improved recognition accuracy compared to other static data types. Among machine learning methods, SVM stood out for its high accuracy, while neural networks showed promise. Comparing classical machine learning methods with neural networks presents challenges due to their varied performance, which is highly dependent on the choice of dataset, measurement criteria, and emotion model. Researchers are advised to choose the approach that most closely aligns with their specific research objectives and the nature of their work.

The current study is limited by the fact that it surveyed the related literature without focusing on a specific measurement and stimuli. This creates a restriction on finding the best machine learning method for emotion recognition. Our results are not broadly generalizable within the scope of machine learning. Notwithstanding these limitations, this work offers valuable insights into trending learning methods, induction techniques, and emotion models.

A further study could assess the comparative effectiveness of VR-based emotion induction to traditional methods. This will enhance our understanding of emotional responses in diverse contexts, contributing to the advancement of the field.

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